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Non-residential Electricity Prices

A Review of Data Sources and Estimation Methods

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1 Introduction

Retail electricity prices are a critical input to any cost-benefit analysis of energy management strategies. For example, life-cycle cost (LCC) analyses are frequently used to evaluate the potential net consumer benefit of investments in energy-saving equipment. The LCC for a piece of equipment is defined as the sum of the total purchase and installation cost, plus the net present value of the lifetime equipment operating and maintenance costs. In evaluating different equipment choices, the additional cost of a more expensive but higher-efficiency design may be offset by reduced operating costs, with the latter primarily determined by the value of energy savings. The LCC is used to quantify consumer benefits in online energy analysis tools such as the *Commercial Buildings Energy Saver* [1], and in policy impact studies such as the Department of Energy's (DOE) Appliance and Equipment Standards rule-making analyses [6].

In the simplest approach, operating cost savings are estimated as the product of the change in kilowatt hours (kWh) consumed, times a commodity price for electricity. In reality, the pricing schemes used by utilities can be considerably more complicated, and reflect the fact that provision of electricity is a service, with supply of the commodity kWh being only one aspect of that service. For non-residential consumers in particular, utility tariffs may incorporate relatively complex formulae for computing the bill from the customer's energy use.

To better understand utility pricing and the marginal value of reductions or shifts in electricity use, Lawrence Berkeley National Laboratory (LBNL) began compiling a database of electricity tariffs, known as the Tariff Analysis Project or TAP, in 2004 [2–4]. From the perspective of database development, the tariff consists of a set of rules and data that specify how the electricity bill should be calculated from the consumer's energy use data. For the non-residential sector, the majority of charges depend on the billing period energy use (kWh) and demand (kW). [1] As reviewed in [2], tariff formulae vary significantly across utility companies, and may require time-of-use rates, especially for larger loads. This implies that the cost of a kWh of electricity depends not only on the tariff rules defined by the provider, but also on the energy use characteristics of specific users. For example, when a tariff includes demand charges, two consumers with the same electricity consumption could have very different average and marginal prices, depending on their demand. The key point is that the price of electricity is a function rather than a number; hence, when evaluating different electricity price data sources, we need to consider whether they provide enough information to understand this functional structure.

In previous work, we have presented a definition of the TAP database structure and how it maps onto typical tariff structures [2], an analysis of non-residential tariffs with application to commercial buildings [3], and a detailed analysis of electricity pricing for the residential sector [4]. This paper presents both an update to the non-residential sector price analysis, and a comparison and evaluation of price estimates derived from two other data sources:

[1] Demand is defined as the maximum power consumption during the billing period. It is typically metered as a 15-minute average. In this paper, for practical reasons, when analyzing load shape effects we define demand based on the one-hour averaged power consumption.

- the Energy Information Administration (EIA) Form 861 annual [9] and monthly [10] data, consisting of revenues, sales and consumer counts by sector for all utilities with sales to final consumers;
- the Edison Electric Institute *Typical Bills and Average Rates* biannual reports [5], which provide the total utility bills at specific consumption levels for a large selection of investor-owned utilities.

These data differ in frequency of collection, coverage of the utility industry, and the level of detail in the description of the consumer population. It is not the aim of this paper to reproduce the types of price estimates and historical trends that are published by the EIA; instead our goal is to use the comprehensive EIA data to evaluate sampling and other potential biases in the smaller-sample data sets, and to use the latter to develop price estimates that cannot be made from the EIA data. More specifically, the goals of this study are to:

- provide precise definitions of different types of price and of their use in estimating the consumer value of electricity savings;
- define price estimation methods appropriate to different data sets;
- quantify the degree of variability in prices due to region, season, and industry structure on the utility side;
- quantify the degree of variability in prices due to baseline energy use and the pattern of changes to energy use on the customer side;
- compare results from different calculation methods and/or data sets, and provide recommendations for use in practice.

The rest of this paper is organized as follows: In Section 2 we provide an overview of how non-residential utility tariffs are structured, and how this leads to a concept we call the *effective marginal price* or EMP. We also present equations defining the EMP as a function of both tariff and consumer data. In Section 3 we review the electricity price data sources, discuss the relationship between the data characteristics and our price estimation methods, and define the averaging methods used to construct state and regional price estimates. As data on non-residential customer characteristics are also needed for this analysis, Section 3 includes a discussion of commercial building data available from EIA's Commercial Building Energy Consumption Surveys [8]. Section 4 presents some additional information on the methodology used in this paper to create a price data set that is (1) relevant to the non-residential consumer population in general and (2) comparable across different data sources. We provide an overview of utility industry structure, how it affects retail prices, and how we adjust for potential sampling bias in TAP and EEI. We define a weighting scheme that allows us to generalize prices computed for specific customer billing data, to prices applicable to customer classes, with the latter defined by load size. We also present the methods used to analyze time-of-use rates, and to evaluate how the distribution of energy use across TOU periods affects the electricity price. In Section 5 we present and compare the results for each data source, review the differences between the samples and methods used for the TAP and EEI data, and discuss how these impact the results. In Section 6 we summarize our findings and present our recommendations for consumer-focused analyses in the non-residential sector.

2 Price Concepts

In our review of residential electricity prices [4] we found that residential consumption varies in the range of a few hundred to a few thousand kWh per month, and there is relatively little impact of the magnitude of consumption on the price. The non-residential sector is very different. For this paper, non-residential is defined as commercial and industrial grid-connected electricity use, which includes commercial buildings of all sizes, industrial buildings, and industrial facilities. For non-residential use the total load connected through a single utility meter can vary from a few kW to tens of thousands of kW. For this reason, utilities generally incorporate an explicit capacity component into their billing, based either on demand charges, or on a rate structure known as *hours charges*. In the latter, block rates are defined for electricity consumption, and the block size is determined as a function of customer demand, which has the effect of increasing the cost of a given quantity of kWh for users with lower load factors[2] (see [3] for examples). Utilities can also more efficiently allocate their time-dependent production costs by requiring non-residential consumers to take service on time-of-use (TOU) tariffs. From the utility's perspective, the structure of a tariff influences how their costs are recovered from different categories of users, which leads to considerable variety and complexity in the way rate structures are specified.

From the user perspective, their contract with the provider results in a monthly bill, which may contain a variety of charges. It is inaccurate to say that consumers are exposed to electricity prices *per se*; given the complexity of many tariffs, it may also be quite difficult for consumers to clearly understand the relationship between their electricity use and the total amount due on the bill. What is clear is that, if a consumer's energy use characteristics change, then their bill will also change. Our goal here is to find a way to reliably capture this difference in the bill, without having to explicitly refer to the details of the tariff specification, and to express it in the form of a price that is straightforward to use in applications. Review of the TAP data shows that, in the vast majority of cases, the major cost determinants are the billing period electricity consumption e and demand d; hence, we represent the bill b as a function of these variables:

$$b = f(e, d). \tag{1}$$

For simplicity we assume that the billing period is a generic calendar month, defined as 30.5 days (365/12). For TOU tariffs, the consumption e is disaggregated across the TOU periods, and the charge applied to the demand depends on the period in which it occurs,

[2]Load factor is defined as the ratio of the average electricity consumption to the demand.

but these are just additional calculation steps, and do not affect the conceptual framework used here.

If the consumer makes a small change to their electricity use from e to e', then they receive a new bill b'. The intuitive notion of a marginal commodity price of electricity p would define

$$b' = b + p(e' - e); \tag{2}$$

the new bill is the old bill plus the price times the change in consumption. By definition a commodity price applies only to the change in consumption, so this formulation of the problem obscures the role that demand plays in determining prices. But it reflects the way people think about electricity pricing and, as we will show, generalizing p from a number to a function allows demand charges to be dealt with in a quantitatively precise manner.

We frame the calculation as it is implemented in TAP, with the tariff function known explicitly. Our notation is:

- the tariff index is i,
- the consumer index is j,
- the billing period index is k,
- the electricity consumption for consumer j during period k is e_{jk},
- the electricity demand for consumer j during period k is d_{jk},
- the utility bill is b_{ijk},

While a single utility has many tariffs, once the consumer data are specified, a unique default tariff is defined, so the tariff index i can also be considered a utility identifier. The billing period is included as an index because many tariffs define seasonal rates. While the specific month assigned to a season depends on the tariff, in general there are only two seasons (summer and winter), so the index k refers to one of these. Given the tariff and the bill input data d and e, the bill itself can be calculated. Given the bill, we define the average electricity price a_{ijk} as the ratio of the total bill to the energy consumption,

$$a_{ijk} = \frac{b_{ijk}}{e_{jk}}. \tag{3}$$

We define a marginal energy price as the incremental change in the bill given an incremental change in consumption, holding demand fixed:

$$u_{ijk} = \frac{\Delta b_{ijk}|_{d_{jk}}}{\Delta e_{jk}}, \tag{4}$$

where the Δ represents a small change of either sign. Similarly, the marginal demand price is the incremental change in the bill given an incremental change in demand, holding consumption fixed:

$$v_{ijk} = \frac{\Delta b_{ijk}|_{e_{jk}}}{\Delta d_{jk}}. \tag{5}$$

Under general conditions, with both d and e changing, the total change in the bill is given by

$$\Delta b_{ijk} = u_{ijk}\Delta e_{jk} + v_{ijk}\Delta d_{jk}. \tag{6}$$

We combine equations (2) and (6) to explicitly relate the price p to the bill data. We refer to this quantity as the effective marginal price (EMP) p_{ijk}. The EMP by definition satisfies the equation

$$\Delta b_{ijk} = p_{ijk}\Delta e_{jk}. \tag{7}$$

Combining equations (6) and (7), and rearranging, gives

$$\Delta b_{ijk} = \Delta e_{jk}(u_{ijk} + v_{ijk}\frac{\Delta d_{jk}}{\Delta e_{jk}}). \tag{8}$$

The second term captures the effect of the demand charges on the EMP. It depends on the ratio of the demand decrement to the consumption decrement; as these can vary independently, mathematically this ratio is an independent variable. It is most conveniently expressed in the form of a *marginal load factor* (MLF), defined as the ratio of the average value of the energy decrement to the demand decrement:

$$x_{jk} = \frac{\Delta e_{jk}}{N_h \Delta d_{jk}}, \tag{9}$$

where N_h is the number of hours in the billing period. The effective marginal price is then

$$p_{ijk} = u_{ijk} + \frac{\hat{v}_{ijk}}{x_{jk}}, \tag{10}$$

where the rescaled demand charge is equal to

$$\hat{v}_{ijk} = \frac{v_{ijk}}{N_h}. \tag{11}$$

The MLF is a dimensionless number, and both u_{ijk} and $\hat{v}_{ijk}$ have the units of \$/kWh. For a demand charge of 10 \$/kW, the rescaled value $\hat{v}$ is 0.0137 \$/kWh.

The MLF is essentially a weighting factor that determines the relative importance of the demand charge at the margin. Upper and lower bounds on the MLF and the EMP can be deduced from simple logical considerations. For a perfectly flat load decrement, the energy savings are equal to N_h times the demand reduction, so $x_{jk} = 1$. This is a physical upper bound for x_{jk}, and corresponds to a minimum value for the EMP of $p_{ijk} = u_{ijk} + \hat{v}_{ijk}$. At the other extreme, if the energy savings were concentrated in a single hour, and this was also the hour of the customer's peak load, then the energy savings equals one hour times the demand savings and $x_{jk} = 1/N_h$. This is a physical lower bound for x_{jk}, which defines the upper bound for the EMP as $p_{ijk} = u_{ijk} + N_h\hat{v}_{ijk} = u_{ijk} + v_{ijk}$. For on-off loads with constant power consumption during the on-time (such as lighting without controls or single speed motors), if x is the percent of hours that the device is on, then the MLF is equal to x (assuming the device is on during the hour of the building peak).

In applications, the value of the MLF is determined by the magnitude of load reduction during the hour that defines the metered peak demand for billing purposes. Based on simulated building data, for end-use based load reductions, the MLF ranges from 0.3 to 0.5 for peaking loads such as cooling and 0.75-0.95 for flat loads such as refrigeration or exhaust fans [3]. Most generally, there may be situations where energy savings occur but do not affect the demand at all, and the MLF is not defined. Conversely, a load shifting measure would lead to demand savings with no energy savings, in which case the commodity price of equation (10) is not relevant. In these special cases the bill savings are still defined by equation (6). In the rest of this paper we assume that both consumption and demand changes are non-zero and base our analyses on equation (10). We treat the MLF as an independent variable, and provide EMP results either as a value for MLF=0.5, or as a curve of marginal price as a function of the MLF.

3 Data Overview

3.1 EIA Form 861 data

The EIA Forms 861 [9] and 861m [10] provide revenues, sales in megawatt hours and consumer counts by sector, organized by utility and by state. The Form 861 data (EIA861) includes annual data for all utilities who sell electricity to final consumers, and the Form 861m data (EIA861m) provides monthly data for a smaller sample consisting primarily of larger utility companies. Sectors are defined as residential, commercial, industrial and transportation. Here we analyze data for the commercial and industrial sectors; we also define a non-residential sector by summing together the commercial and industrial data for each utility.

The EIA data can be used to generate a utility-level retail price for each sector by dividing the total revenues by the total sales. We use the index u to refer to a given utility. The EIA861 data correspond to a sum across all customers, tariffs, and billing periods within each sector. Defining r_u as revenues, and e_u as sales,

$$r_u = \Sigma_i \Sigma_j \Sigma_k \, b_{ijk}, \tag{12}$$

and

$$e_u = \Sigma_i \Sigma_j \Sigma_k e_{jk}. \tag{13}$$

The price estimate based on these data is the ratio of the two. Using the definition of average price in equation (3) we can write the utility-level price for utility u as

$$a_u = \frac{r_u}{e_u} = \frac{\Sigma_i \Sigma_j \Sigma_k e_{jk} a_{ijk}}{\Sigma_i \Sigma_j \Sigma_k e_{jk}}. \tag{14}$$

This formula shows that a_u is a consumption-weighted average of a_{ijk} over all the utility's customer bills for a year.

We construct regional averages for all data sets using the EIA861 data to weight individual utilities. In our analysis of residential electricity prices we used consumer counts to weight

Table 1: Region definitions used for regional averaging. The label PAC* refers to the Pacific region without California.

Code	Region Name	States	Short Name
0	United States	All	USA
1	New England	CT, MA, ME, NH, RI, VT	NE
2	Middle Atlantic	NJ, PA, NY	MATL
3	East North Central	IL, IN, MI, OH, WI	ENC
4	West North Central	IA, KS, MN, MO, ND, NE, SD	WNC
5	South Atlantic	DC, DE, FL, GA, MD, NC, SC, VA, WV	SATL
6	East South Central	AL, KY, MS, TN	ESC
7	West South Central	AR, LA, OK, TX	WSC
8	Mountain	AZ, CO, ID, MT, NM, NV, UT, WY	MTN
9	Pacific	AK, HI, OR, WA	PAC*
10	California	CA	CA

the data, so that the average would correspond to the price paid by a typical consumer [4]. For the commercial and industrial sectors it is less clear that consumer-weighting gives a good estimate of the value of electricity savings for analyses of typical end-use or building-envelope efficiency measures. The metrics used in cost-benefit analysis are typically defined on a per-unit of equipment basis; this is the case for example with the DOE's efficiency standards program [6]. This means that the impacts of energy-saving measures are calculated for each piece of equipment installed, and the energy price should represent the value likely to be applied to that piece of equipment. There is a wide range of total connected load in the non-residential sector, and it is reasonable to suppose that larger loads correlate with larger facilities, meaning more activity, employees, and equipment. Hence, a weighting that reflects customer size seems more appropriate for the non-residential sector. Here we use the EIA sales data to weight the contributions of individual utilities to define regional-average prices. Regions are defined as census divisions with one exception; results for California are reported separately from the rest of the Pacific census division.[3] Table 1 defines the state assignment and the codes used in the charts and tables. For regionally averaged quantities we use the index R to denote the region. For example, the sales-weighted regional average of a_u is

$$a_R = \frac{\Sigma_{u \in \mathrm{R}} e_u a_u}{\Sigma_{u \in \mathrm{R}} e_u}, \tag{15}$$

The EIA861m monthly data can be used to evaluate seasonal variation in the utility-level and regional price. We assign the months May through September to summer and the rest of the year to winter. This is consistent with the TAP data, which show that for almost all tariffs the summer season is five months long (all seasonal tariffs define June through September as summer, and one half to two thirds of seasonal tariffs define either May or October as a summer month). We define seasonal average prices by first taking a simple average of the monthly data for the summer or winter season, and then using equation (15)

[3]We use the abbreviation PAC* to denote the Pacific census division without CA.

Table 2: Color-coded values of the percent difference between the summer/winter price and the annual price; blue (red) indicates that the seasonal value is lower (higher) than the annual.

Sector	Region	2008 Summer	2008 Winter	2012 Summer	2012 Winter	2016 Summer	2016 Winter
Commercial	1 NE	8.7%	-6.1%	-1.1%	0.7%	-3.8%	2.5%
	2 MATL	9.6%	-7.5%	3.3%	-2.7%	2.2%	-1.9%
	3 ENC	-3.8%	-3.3%	2.0%	-1.6%	1.0%	-0.8%
	4 WNC	11.6%	-9.1%	9.7%	-8.1%	9.3%	-7.5%
	5 SATL	4.2%	-3.5%	0.2%	-0.2%	-1.1%	0.8%
	6 ESC	6.8%	-5.8%	0.0%	0.0%	-0.8%	0.7%
	7 WSC	9.2%	-8.6%	-0.8%	0.7%	1.7%	-1.6%
	8 MTN	4.8%	-4.8%	3.8%	-3.2%	3.2%	-2.6%
	9 PAC*	3.6%	-2.8%	0.0%	0.0%	-0.9%	0.6%
	10 CA	11.9%	-9.8%	13.7%	-11.4%	9.0%	-7.0%
Industrial	1 NE	16.2%	-7.8%	-1.3%	1.3%	-1.6%	1.3%
	2 MATL	9.5%	-5.9%	-2.6%	1.2%	3.7%	-2.8%
	3 ENC	3.8%	-4.0%	3.2%	-2.4%	2.1%	-1.1%
	4 WNC	12.9%	-9.8%	9.4%	-7.1%	12.0%	-7.7%
	5 SATL	5.8%	-4.4%	1.9%	-1.3%	1.9%	-1.5%
	6 ESC	12.5%	-9.2%	1.8%	-1.4%	1.5%	-1.0%
	7 WSC	12.4%	-10.1%	2.1%	-1.7%	3.8%	-2.9%
	8 MTN	11.5%	-13.7%	10.2%	-12.5%	8.0%	-9.7%
	9 PAC*	-0.6%	0.5%	0.0%	-0.1%	0.1%	-0.3%
	10 CA	9.7%	-7.7%	8.2%	-4.6%	11.4%	-11.1%

to define the regional values. This EAI861m data are summarized in Table 2. The entries in the table show by how much the summer/winter price differs from the annual average,for the years 2008, 2012 and 2016. The color-coding in the table is red for positive differences, blue for negative, and white for zero. The table shows that in most regions summer prices are higher and winter prices lower. The table also shows that the degree of seasonal variation seems to be moderating, and in some regions (notably NE), winter prices are higher in 2016. In 2016 the largest variation occurs in regions 4 and 10, where summer prices are 8-12% higher and winter prices 7-9% lower than the annual average. This degree of seasonal variation is consistent with what we see in the TAP and EEI data; as end-use loads can also have strong seasonal variation, we retain the seasonal dependence in our price analyses.

In principle the EIA861m monthly data can also be used to estimate a version of the marginal commodity price, defined as the slope of a line fitted to the monthly revenues and sales data. We have performed these calculations using a robust method, the Theil-Sen estimator [11], which is less sensitive to noise than ordinary least squares.[4] The analysis

[4]The Theil-Sen estimator is the median slope of the set of lines passing through all data pairs in the sample.

shows that there is a great deal of volatility in the estimated marginal prices, with year-to-year variations as large as a factor of two in some regions. As no other data set shows this level of volatility, we conclude that the EIA861m data cannot be used to estimate marginal prices.

3.2 Edison Electric Institute Typical Bills

The Edison Electric Institute (EEI) publishes a *Typical Bills and Average Rates* report for summer and winter each year [5]. The data in these reports consist of the total consumer bill at fixed consumption and demand levels for approximately 200 utilities, all of which are investor-owned. The EEI consumption and demand levels and associated load factors are presented in Table 3. The first column defines a bill index, which is equivalent to the consumer index j in our notation, and ranges from 1-32. The table is sorted by increasing demand, and includes the demand, energy and load factor for each bill. The set of bills contains those published by EEI, plus a set of additional bills calculated with TAP. For reference, the last two columns provide the bill sector and index as assigned by EEI in their data. The bin indices in the table are discussed in the Section 3.4; the other fields (bill group, TAP and EEI weights) are discussed in Section 4.2.

For the EEI data we estimate average prices using equation (3). To estimate the marginal energy price, we apply the method of equation (4) to pairs of bills with the same demand but different levels of consumption. This means we can only estimate independent marginal prices for some of the EEI bills. Estimating marginal demand prices from the EEI data is more complicated; because there are no pairs of bills having the same consumption and different demand, equation (5) can't be applied. Instead, we use a regression-based approach. For each year, utility and season, the steps are as follows:

1. In this calculation j is the bill index, e_j is the consumption, d_j is the demand, b_j is the bill, and u_j is the calculated marginal energy price. For bills which do not have an independently calculated value of u_j, we use the value available for a bill with the same demand and closest consumption.

2. For each bill b_j we define a residual q_j as the difference $q_j = b_j - u_j e_j$.

3. The non-negative residuals q_j are then grouped according to the range of demand values, ignoring sector. The low demand range is defined as 3-75 kw and uses bills 2, 10 and 14. The medium demand range is defined as 75-1000 kw and uses bills 14, 21, 22 and 24. The large demand range is defined as 500-50000 kw and uses bills 22, 24, 30 and 31.

4. We calculate the slope of the line passing through the pairs (q_j, d_j), which provides an estimate of the demand charge in each demand range.

This calculation generally leads to positive or zero values; we interpret the latter as a genuine lack of demand charges for that utility. In some cases, the method produces small

Table 3: List of bills used in the EEI and TAP price analysis. The Load Factor and Log10 Demand bins refer to the distribution illustrated in Figure 1. Each bill is assigned to a Bill Group corresponding to a low, medium or high demand range. The numbers in the TAP and EEI weight columns define the weight used to average over bills within a billing group.

Index	Log10 Demand	Demand kW	Energy kWh	Load Factor Bin	Log10 D Bin	Bill Group	TAP Weight	EEI Weight	EEI Sector	EEI Index
1	0.48	3	375	1	2	A	0.0207	0.0207	com	1
2	0.48	3	1,500	4	2	A	0.0556	0.1268	com	2
3	1.10	13	922	1	5	A	0.0998			
4	1.10	13	2,765	2	5	A	0.1164			
5	1.10	13	4,608	3	5	A	0.0521			
6	1.34	22	11,273	4	6	A	0.0321			
7	1.34	22	14,494	5	6	A	0.0017			
8	1.50	32	2,765	2	7	A	0.0588			
9	1.60	40	10,000	2	8	A	0.0438	0.2997	com	3
10	1.60	40	14,000	3	8	A	0.0731	0.1575	com	4
11	1.74	55	4,026	1	8	A	0.0459			
12	1.74	55	28,182	4	8	A	0.0392			
13	1.88	75	15,000	2	9	A	0.0531	0.0615	ind	1
14	1.88	75	30,000	3	9	A	0.0584	0.0844	ind	2
15	1.88	75	50,000	5	9	A	0.0023	0.0023	ind	3
16	2.34	220	16,104	1	11	B	0.0137			
17	2.34	220	48,312	2	11	B	0.0405			
18	2.34	220	80,520	3	11	B	0.0404			
19	2.54	350	179,340	4	12	B	0.0504			
20	2.54	350	230,580	5	12	B	0.0081			
21	2.70	500	150,000	3	13	B	0.0136	0.0273	com	5
22	2.70	500	180,000	3	13	B	0.0081	0.1475	com	6
23	3.00	1,000	200,000	2	15	C	0.0104	0.0104	ind	4
24	3.00	1,000	400,000	3	15	C	0.0216	0.0489	ind	5
25	3.00	1,000	650,000	5	15	C	0.0052	0.0052	ind	6
26	3.10	1,259	645,073	4	15	C	0.0216			
27	3.72	5,248	5,233,034	5	18	C	0.0039			
28	3.90	7,943	2,907,241	3	19	C	0.0019			
29	3.90	7,943	4,070,138	4	19	C	0.0042			
30	4.70	50,000	15,000,000	3	22	C	0.0013	0.0017	ind	7
31	4.70	50,000	25,000,000	4	22	C	0.0022	0.0022	ind	8
32	4.70	50,000	32,500,000	5	22	C	0.0000	0.0039	ind	9

negative values, which we treat as zero. Additional tests show that the estimated marginal demand charge is not sensitive to details of the choice of bills used in the calculation.

This approach provides average prices for all EEI bills, marginal energy prices for some bills, and marginal demand prices for three demand ranges. These data are aggregated to the regional level using the EIA861 sales data to weight the contribution of each utility. The EEI reports are seasonal, providing summer and winter prices. We also report annual values, defined as (5/12) times the summer value plus (7/12) times the winter values. Further adjustments to the data are discussed in Section 4.

3.3 TAP

The TAP database consists of over 2,000 tariffs collected for 150 utilities, covering both investor-owned and publicly-owned companies, for three data years. The sample is designed to provide good coverage of the industry at the level of census division. The information in the tariffs is stored in a set of normalized data tables that can accommodate most of the features (seasonal rates, time-of-use, block rates *etc.*) used in real tariffs [2]. Utilities typically do not define tariffs as commercial or industrial; instead they use a general non-residential category for both. Customers are assigned to specific tariffs based on their electricity use, most often by their peak annual demand; for smaller customers the assignment may be based on the annual electricity consumption [3]. These assignment rules are recorded in the TAP database, and used to match billing data to the correct tariff. Within TAP, for each utility included in the sample, we collect the set of default tariffs that provide complete coverage of the demand up to 50,000 kW (if available).

The most recent year in which TAP data were collected is 2015; for this year the sample includes 137 utilities and a total of 400 tariffs. Approximately 1/3 of the utilities are investor-owned, and the rest are publicly-owned. For a significant number of utilities, the default tariff is time-of-use; the count of TOU tariffs is tabulated in Table 4. The table shows both the count of tariffs, and the percent of electricity sales, for those utilities with default TOU tariffs across three customer size groups. Group A corresponds to users with demand less than 100 kW, Group B to demand between 100 kW and 1000 kW, and Group C to demand larger than 1000 kW. The TAP data do not include any variant of real-time pricing, as no utility currently offers this type of tariff as a default.

The TAP database is the only electricity price data set that allows the marginal value of changes in electricity demand and consumption to be calculated without approximation. TAP bill calculation tools are used to calculate the bill for each of the 32 bills listed in Table 3. Marginal energy and demand prices are computed by applying a 3% decrement to either the demand or the energy, recalculating the bill, and using equations (4) and (5). Regional averages of these prices are calculated using the sales data from EIA861 to weight the individual utilities. For all tariffs, annual, summer and winter prices are defined. For tariffs with seasonally varying rates, the annual price is defined as (5/12) times the summer value plus (7/12) times the winter value. For tariffs that do not vary with season, the summer and winter prices are simply set equal to the annual values. Our approach to developing the necessary inputs for TOU tariffs is described in Section 4.3.

Table 4: Count of tariffs that are default TOU, by customer class. The table also includes the percent of sales (relative to the total TAP sample) for those utilities with default TOU tariffs.

	Percent of Sales		**Count of Tariffs**	
Bill Range	**Non-TOU**	**TOU**	**Non-TOU**	**TOU**
A only	94%	6%	127	4
A to B	89%	11%	67	3
A to C	95%	5%	61	3
B only	37%	63%	17	10
B to C	63%	37%	36	14
C only	66%	34%	44	19

3.4 CBECS

In estimating non-residential prices, the energy use characteristics of the user are required input data. To better understand what prices are actually seen by these consumers, information is required regarding the baseline electricity use characteristics of commercial and industrial enterprises. To obtain this information, we use data from three EIA Commercial Building Energy Consumption Surveys (CBECS) [8], for years 1992, 1995, and 2012. Each survey consists of several thousand individual buildings, stratified by region and type, and assigned a weight that represents the number of comparable establishments in the population. The most recent data, for survey year 2012, are used to calculate relative weights for the number of establishments by region and building type. Only the surveys of 1992 and 1995 provide electric utility billing data that include both billing period consumption and demand. These data are combined with the building weights from the 2012 survey to estimate the distribution of billing period consumption and demand across the building population.

The CBECS 1992 and 1995 billing data are normalized by converting the reported billing periods to calendar months as described in [3], and filtered to remove outliers. To characterize each building we use the baseline demand (which is needed to determine the appropriate tariff) and the baseline load factor. The latter is denoted L_{jk} and defined by the equation

$$L_{jk} = \frac{e_{jk}}{N_h d_{jk}}. \tag{16}$$

This is similar to the definition of the MLF in equation (9), but uses baseline quantities rather than decrements. We previously found that, for a given level of demand, the load factor is a better predictor of the marginal electricity price than the energy consumption [3].

4 Methodology

The building data from 1992 and 1995 surveys are mapped onto CBECS 2012 using a re-weighting scheme. We first assign each building type in each sample to a more generic type, as defined in Table 5. The table indicates which building types (referred to as

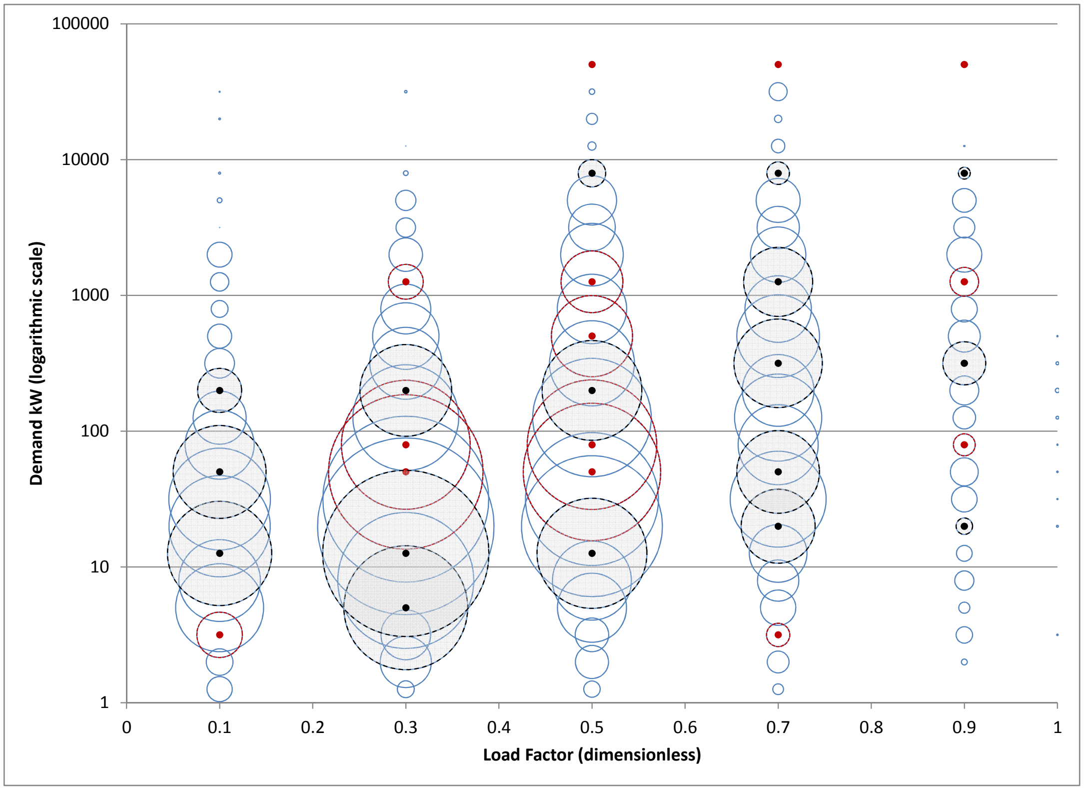

Figure 1: Distribution of the monthly bills as a function of demand and load factor based on CBECS 2012 weights. The data are binned; each circle represents one bin, centered at the bin center, with the size indicating the total weight in that bin. The small red disks indicate the data for the bills included in the EEI data. The small black disks indicate additional bills calculated using TAP data.

principle building activity in the survey data) are present in each survey, and the generic type that they are assigned to here. Each building is also assigned to a vintage category, with category 1 defined as pre-1980 and category 2 as 1980 and newer. Finally, each building is assigned to a census division, which is the region descriptor used in CBECS. The total weight in each sub-category, defined by generic building type, census division, and vintage is calculated both for the sample of 1992 and 1995 buildings with bill data, and for the CBECS 2012 sample. The building weights in the billing data are then re-scaled so that the percentage of all buildings in each sub-category is the same between this sample and the CBECS 2012 full sample.

The next step is to bin the billing data, so as to define a distribution in the demand/load factor plane. Demand bins are defined logarithmically to better resolve the wide range of variation in this variable, with each factor of ten divided into five bins. The load factor range of zero to one is divided into five bins of width 0.2. The weight in each bin is defined

Table 5: Definition of the building types included in each CBECS survey, and how these are mapped to generic building types for this analysis.

Code	Building Activity	CBECS 1992	CBECS 1995	CBECS 2015	Building Type
1	Vacant	x	x	x	Exclude
2	Office/Professional	x	x	x	Office
3	Mercantile/services	x			Mercantile
4	Laboratory	x	x	x	Other
5	Warehouse (nonrefrig.)	x	x	x	Other
6	Food Sales	x	x	x	Food
7	Public order and safety	x	x	x	Other
8	Health care (Outpatient)	x	x	x	Health
9	Industrial processing/manufact.		x	Exclude	
11	Warehouse (refrig.)	x	x	x	Other
12	Religious worship	x	x	x	Public
13	Public assembly	x	x	x	Public
14	Education	x	x	x	Public
15	Food services (Restaurants)	x	x	x	Food
16	Health care (Inpatient)	x	x	x	Health
17	Nursing home	x	x	x	Lodging
18	Lodging (Hotel/motel/dorm)	x	x	x	Lodging
19	Residential	x			Exclude
20	Indoor parking garage	x			Exclude
21	Other	x			Other
23	Strip shopping		x	x	Mercantile
24	Enclosed shopping ctr/mall		x	x	Mercantile
25	Retail (excluding mall)		x	x	Mercantile
26	Service (excluding food)		x	x	Mercantile

as the count of bills for a given building that fall into that bin, multiplied by the CBECS building weight. The resulting distribution is plotted in Figure 1. In this figure the load factor is plotted on the horizontal axis and the log of demand on the vertical axis. The bin centers correspond to a grid of points, and the weight assigned to each bin is represented by a circle centered on the grid point. The area of the circle corresponds to the weight, and empty bins do not show up on the plot. The chart captures the energy use characteristics for the population of commercial buildings. It shows that the majority of buildings have baseline load factors of 0.5 or below, and that there is a small positive correlation between demand and load factor.

This visualization can also be used to indicate the degree to which the EEI bills are representative of bills in the general building population. We identify the locations of the bins that contain an EEI bill using a small red disk at the bin center, and a red outline on the circle. The three red circles at the top of the chart correspond to industrial EEI bills with demand of 50,000 kW, which do not have any corresponding bills in the CBECS data. The load factor bin centered at 0.5 is well covered by EEI data, but there are significant numbers of buildings with load factors around 0.1, 0.3 and 0.7 without corresponding bills in EEI. It is possible that the prices calculated from the EEI would be valid for these other bins, but the EEI data are not sufficient to determine this. This is where the TAP database becomes very useful. As TAP contains the full specification of the tariff, we can use these data to investigate whether electricity prices vary strongly as the electricity use data move around in this plane. We use the TAP data to calculate an additional set of bills at the bin centers indicated in Figure 1 by small black disks surrounded by shaded circles. The full set of 32 bills used in the analysis are listed in Table 3.

In this section we present some additional information about the methodology used to construct comparable price estimates across each data set. The limitations on the TAP and EEI samples, and our approach to correcting for these, are presented in Section 4.1. As illustrated in Figure 1, the EEI data are provided in the form of individual bills with specific values of consumption e and demand d, shown as red disks in the figure. To enable comparison, we use the TAP data to compute the same set of bills. To further investigate variability in prices as a function of the baseline bill data, we use TAP to compute the additional bills listed in Table 3, and represented by the black disks in Figure 1. Section 4.2 discusses the method used to weight individual bills to create prices representative of customer classes. Section 4.3 present some additional detail on our methods for calculating TOU bills in TAP.

4.1 Utility Industry Structure

Broadly speaking, the utility industry can be segregated into two types of provider and two types of service. The two types of provider are privately- and publicly-owned companies. The EIA861 data assign each company an ownership type, with all investor-owned utilities (IOUs) and power marketers privately owned, while the publicly-owned utility (POU) sector consists of cooperatives and municipal, county, state and federal agencies. The two types of service are bundled and unbundled. For bundled service both the supply and the delivery of energy are provided by the same company; in unbundled service they are provided by different companies. For customers taking unbundled service, there is no public data source describing how energy and delivery service providers are paired, so there is no way to determine the total bill. For this reason both the EEI and the TAP data cover bundled service only.

We use the EIA data to evaluate whether there are systematic differences in price based on provider and service type. Because EIA tabulates each utility's data by state, at the state level the total sales and consumer counts for unbundled delivery service should equal the total sales and consumer counts for unbundled energy supply (EIA includes an adjustment to enforce this identity). We use these data to define a single *unbundled utility* for each state. The revenues to this unbundled utility are equal to the sum of revenues for energy and delivery, and an average price is defined as in equation (3). We define average prices at the regional level for public and private bundled service by including only the appropriate subset of utilities in the sum of equation (15).

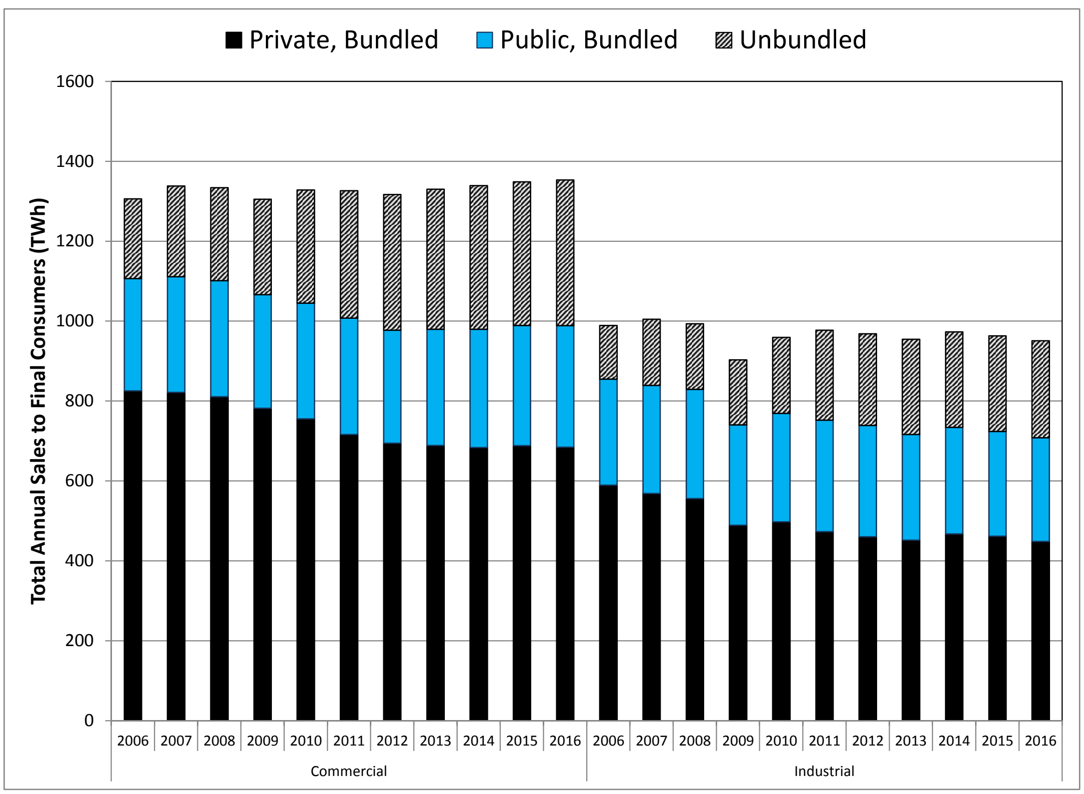

Figure 2: Total annual sales in TWh for non-residential bundled service provided by public and private companies, and for unbundled service.

The comparison of private/public bundled and unbundled service is summarized in

Figures 2 and 3. Figure 2 shows time series of total commercial and industrial sales in TWh for bundled service provided by public and private companies, and for unbundled service. Unbundled service may be provided by a mix of public and private companies; in most cases energy is supplied by a private entity, and delivery may be provided by either a private or a public entity. Unbundled market share grew from 9% of sales in 2006 to 20% in 2013, and has held steady at that level through 2016. Looking at consumer counts rather than sales, the market share of unbundled service was 8% in 2006 and has been at 15% since 2014. This implies that the nonresidential customers taking unbundled service tend to have larger consumption than average, which makes sense, as larger consumers are better positioned to negotiate contracts. Figure 3 shows the annual sales-weighted average price calculated from EIA861 data by region. In this figure the data are color-coded blue for the commercial sector and red for the industrial sector. For each sector three price time series are shown for private bundled service (IOU, filled markers), public bundled service (POU, crosses), and unbundled service (open markers). Data are plotted for every other year for the period 2010 to 2016. Overall it is clear that prices are lower in the industrial sector than the commercial sector, but beyond that there are no clear systematic trends in the data. Prices vary strongly with region, so it is important to retain regional variation in the analysis.

The data from EEI represent private, bundled service only. While the data from TAP include public, bundled service, this sector tends to be under-represented in the tariff data because of the large number of small public utilities. Based on EIA 2016 data, 27% of non-residential customers are served by POUs and the number of POU companies is about 7 times the number of IOUs, implying that the number of customers served by the average POU is about 1/17 that of the average IOU. Hence, for a sample of utilities to cover similar proportions of IOU and POU customers, it would be necessary to sample 4 or 5 POUs for each IOU.

The price differences evident in Figure 3 and the limitations on the TAP and EEI samples may lead to bias in the marginal price estimates developed from the data. We adjust for this by developing correction factors from the EIA data. To correct the EEI data for not sampling the public sector, we define a correction factor for each region as the ratio of the average price calculated from all EIA861 bundled service to that price calculated using only private-sector (IOU) bundled service. This factor is applied to all the EEI price estimates. For the TAP data, we use a different procedure to correct for under-sampling of the public sector. We first define separate sales-weighted regional average prices for the publicly- and privately-owned utilities included in the TAP sample. We then average the regional IOU and POU prices, using the total sales by provider type from EIA861 to weight each sector. This step ensures that the relative weight of public *vs.* private sector utilities is the same in the TAP calculation as it is in the full EIA861 sample. A second correction factor is applied to both the TAP and EEI price estimates, to adjust for potential bias from sampling only bundled service. The second factor is defined as the ratio of the regional average price calculated from all EIA861 service to that price calculated using only bundled service.

Figure 4 shows time series of the correction factors for each region. To make the figure

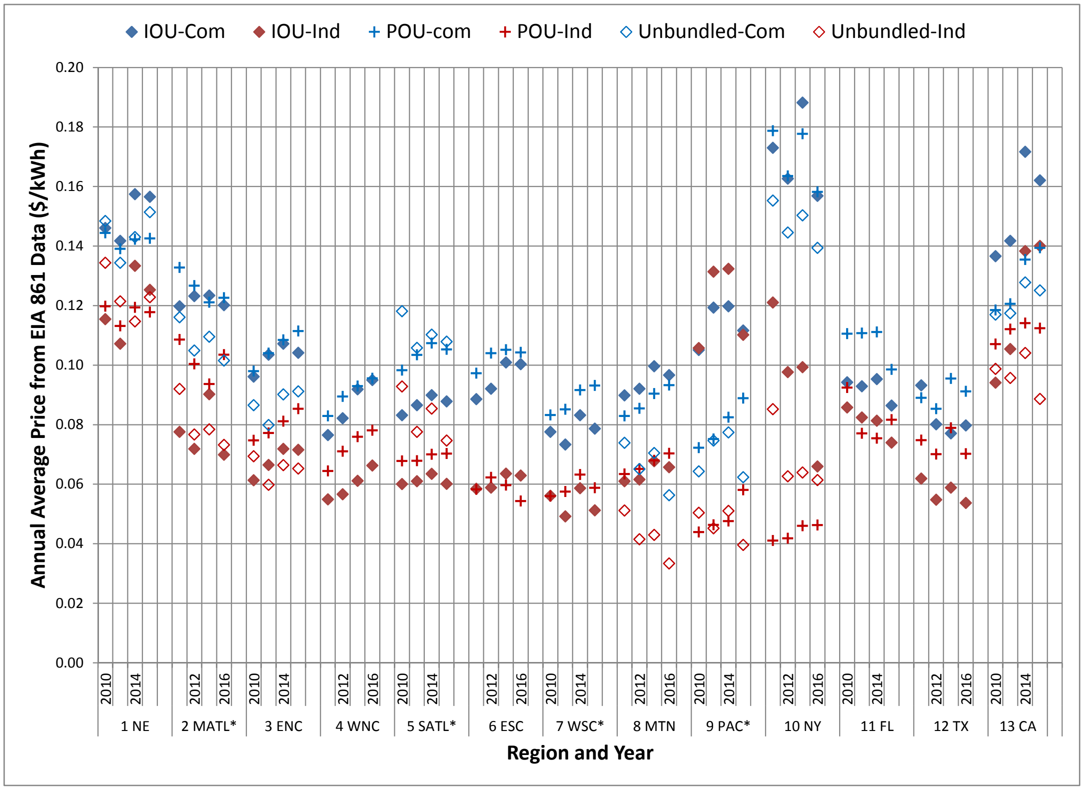

Figure 3: Regional average prices in $/kWh for the commercial and industrial sectors, for private bundled service (IOU, filled markers), public bundled service (POU, crosses), and unbundled service (open markers). Data are plotted for every other year for the period 2010 to 2016.

more legible, two vertical axes are used. The commercial sector data are plotted with solid lines, and the industrial with dashed lines. The black lines (left-hand axis) show the ratio of prices for all bundled service to IOU-only bundled service, which is applied to the EEI data. This number indicates the magnitude of the effect of leaving publicly-owned companies out of the price calculations; when this ratio is greater than one, it means that POUs charge more than private sector companies. In most regions the ratio is within +/- 10% of one, except in region 9 (PAC*) where a few public entities sell industrial power relatively cheaply. The red lines (right-hand axis) show the ratio of prices for all service to bundled-only service, which is applied to both EEI and TAP. This ratio indicates the magnitude of the effect of leaving unbundled service out of the price calculations. The range of variation in all regions is within +/- 10% (refer to the left-hand axis). Regions 1, 2 and 3 (northeastern US) show considerable volatility in this coefficient.

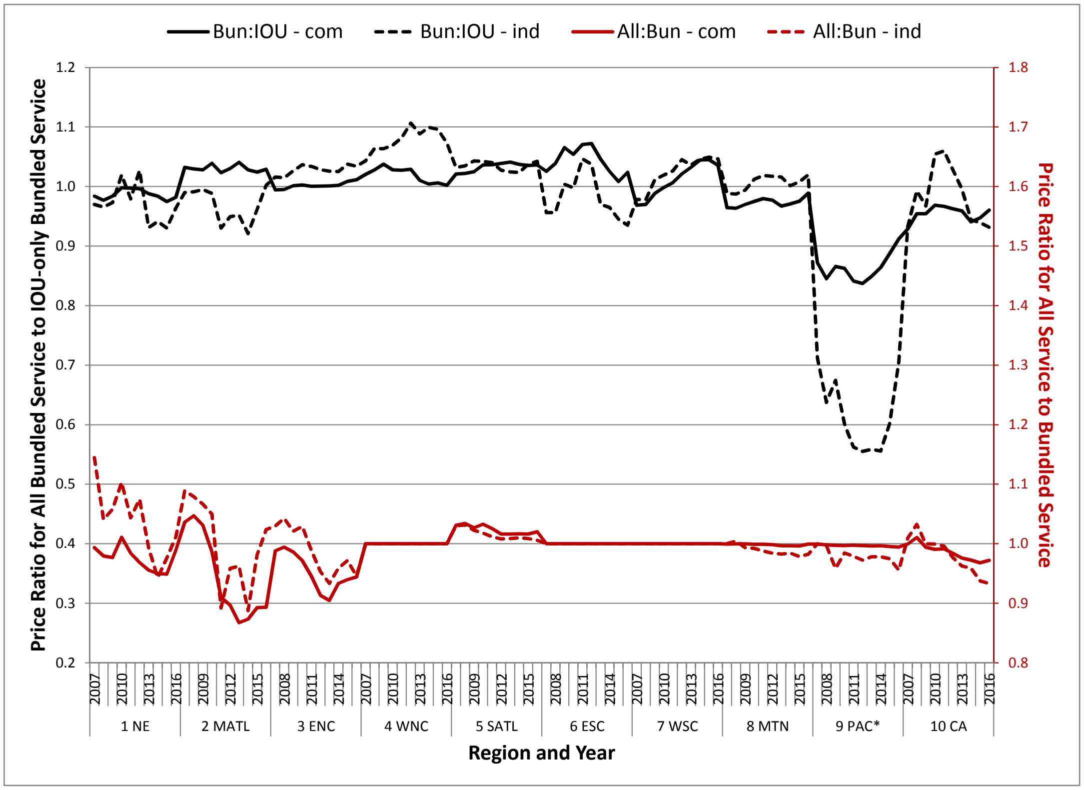

Figure 4: Price ratios derived from EIA861 data. The commercial sector data are plotted with solid lines, and the industrial with dashed lines. The black lines (right-hand axis) show the ratio of prices for all bundled service to IOU-only bundled service.The red lines (left-hand axis) show the ratio of prices for all service to bundled-only service.

4.2 Bill Weighting

We have calculated regional average marginal prices for each of the TAP bills; the detailed results are presented in Tables 10 and 11 in the Appendix. These results show that marginal prices are frequently constant over a range of bills, or equivalently, demand and consumption values. Hence, it is appropriate to convert the prices defined for a specific set of bills into prices that are defined for a range of consumer bills. To develop such representative prices, we define three bill groups, based on the general trends visible in the data of Tables 10 and 11. The bill groups are labeled A, B and C, and correspond to three demand ranges (the bill group is also listed in Table 3). Group A contains bills with demand less than 100 kW, Group B contains bills with demand between 100 kW and 1000 kW, and Group C contains bills with demand larger than 1000 kW.

To present results by bill group, we need to aggregate over the individual bills within the TAP and EEI samples. To do so we apply a variant of the procedure that was used to create the distribution shown in Figure 1. The only difference is that the bins are enlarged to ensure that every bin contains a TAP bill or an EEI bill, as appropriate. The resulting weights are included in Table 3, and plotted in Figure 5.

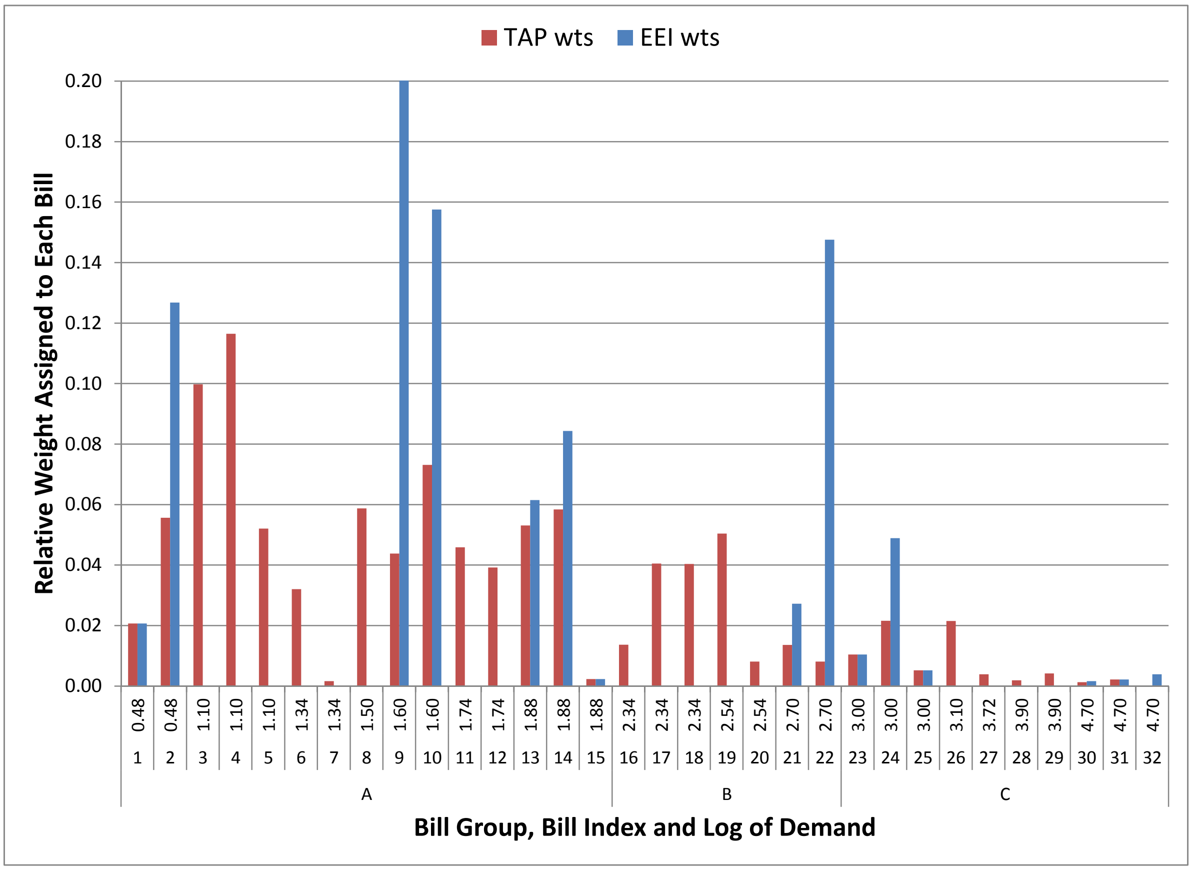

Figure 5: Relative weight attached to each individual bill in the TAP sample (red bars) and the EEI sample (blue bars). These weights are based on the distribution of CBECS bills illustrated in Figure 1.

Defining z as the group index, the bill group averages for each utility (i) and season (k) are defined as

$$P_{izk} = \Sigma_{j \in z} w_{jz} a_{ijk} \tag{17}$$

where w_{jz} is the weight assigned to bill j in Group z, shown in Table 3. In aggregating the data to the regional level, we have a choice of weighting each utility by its commercial, industrial, or combined non-residential sales. As it seems reasonable to associate smaller loads with commercial buildings and larger loads with industrial facilities, we use the commercial sales data to weight utilities for the bills in Group A, and industrial sales to weight utilities for bills in Group C. For the Group B intermediate range, we use the combined non-residential sales to weight individual utilities.

We also define a Group D as the average over bill groups A, B, and C. One option for this averaging procedure is to use the CBECS weights to define the relative contribution of each bill group. However, that approach effectively assumes that all non-residential customers share the characteristics of commercial buildings, which is not necessarily the case. It also ignores the fact that different regions have different proportions of commercial and industrial activity. As an alternative we define a weighting scheme that makes use of the sales and consumer count data available in EIA861. The goal of this scheme is to allocate a fraction of each utility's commercial and industrial sales to each of the bill groups. We can then total the sales by bill group and by region to come up with relative weights for each bill group within each region.

We first define, for each utility and sector, the average annual electricity use per consumer as the ratio of sales to consumers. Using equation (16), and assuming a load factor of 0.5 for commercial and 0.65 for industrial, this number is converted to an average peak demand per customer. In the next step, we segregate the utilities into groups, based on the magnitude of their average demand and the number of customers. The demand ranges are the same as those used to define the bill groups, and the customer count ranges are less than 300, 300-3000, and above 3000.[5]

The value of average demand per customer, combined with the number of customers, places constraints on the fraction of customers that can be assigned to each bill group. In principle, for each utility the average demand could be calculated by first segregating customers into bill groups, calculating an average demand within the bill group, and then averaging the bill groups together. We construct an approximation to this process as follows: first, we define a representative demand value for each bill group of 50 kW for group A, 500 kW for group B, and 5000 kW for group C. Next, we define test values of the weights for each bill group within each utility sub-sample, and calculate the average demand for the sub-sample using the representative demand values. We also calculate the average demand for each sub-sample directly from the EIA data, using consumer counts to weight the average over utilities. Then, we adjust the test weights to better match the average calculated from EIA data. Finally, we use the weights to allocate the sales for each utility to a bill group.

The results of this approach are shown in Table 6 and Figure 5. The last two columns of Table 6 show the average demand for that sub-sample calculated by weighting the representative values *vs.* the values obtained from the EIA data. For example, the first row in the table corresponds to utilities with fewer than 300 customers and an average demand per customer of less than 100 kW. The sub-sample average demand for this group of utilities is 24kW. This closest we can get to this value is to weight bill group A at 100%, and the others at zero, which leads to a weighted average across the representative demand values of 50 kW. The relative weights resulting from this calculation are shown in Figure 5. The figure includes, for comparison, the bill group weights derived from the CBECS data.

[5] There are no utilities with average demand $>$ 1000 and more than 3000 customers.

The weights in this figure are used to construct average (Group D) values of average and marginal prices. These can be considered representative of the non-residential sector, without regard to load size.

Table 6: Parameters used to partition EIA sales data over billing groups. The resulting group weights are shown in Figure 6.

Categories		Bill Group Proportions			Average Demand	
Demand Size	Customer Count	A	B	C	Table	EIA Data
A: D < 100	1: N < 300	1	0	0	50	24
A: D < 100	2: N ≤ 3000	1	0	0	50	14
A: D < 100	3: N > 3000	1	0	0	50	17
B: D ≤ 1000	1: N < 300	0.3	0.7	0	365	366
B: D ≤ 1000	2: N ≤ 3000	0.3	0.7	0	365	363
B: D ≤ 1000	3: N > 3000	0.5	0.5	0	275	296
C: D > 1000	1: N < 300	0.1	0.1	0.8	4,055	4,250
C: D > 1000	2: N ≤ 3000	0.4	0.25	0.35	1,895	1,829

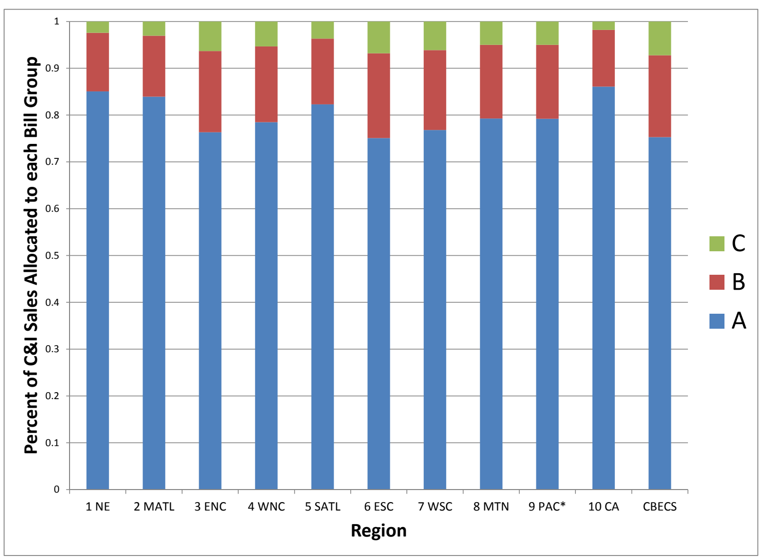

Figure 6: Relative weight attached to each bill group by region. These weights are based on the EIA861 commercial and industrial sales data.

4.3 Time-of-Use Prices

Over 50 tariffs in the TAP database are TOU. These are offered by a variety of utilities for a range of customer sizes; typically TOU pricing is required for larger customers. With TOU tariffs, each hour of the day is allocated to one of two or three periods (on-peak, off-peak and shoulder) and the rate charged for electricity varies by period. Both the hours allocated to a given period and the rates charged may vary by season. Most commonly, summer weekday afternoons are in the on-peak period, and evenings and weekends are in the off-peak period, but there is considerable variation by utility. Table 7 illustrates the allocation of hours for a random selection of tariffs in the TAP database. In this figure, the column labels 1-24 represent the hours of the day with hour 1 corresponding to midnight-1am *etc.* The TOU specification includes the season and the days of the week in which the period definitions are to be applied; days not included in the 'Peak Days' column are all off-peak.

Table 7: Definition of off-peak, shoulder and on-peak hours, denoted (0, 1, 2) in the chart, for a few randomly chosen TAP tariffs. The labels 1-24 correspond to the hours 12-1 AM, 1-2 AM *etc.* This figure illustrates the variability in how TOU periods are assigned, which may depend on season and day-of-week as well as hour-of-day.

Tariff ID	Season	Peak Days	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	All-year	Mon-Fri	0	0	0	0	0	0	0	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1
2	All-year	Mon-Fri	0	0	0	0	0	0	2	2	2	2	2	1	1	1	1	2	2	2	2	0	0	0	0	0
3	All-year	Mon-Sat	0	0	0	0	0	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	0	0	0
4	All-year	Mon-Sun	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	0	0	0	0
5	Summer	Mon-Fri	0	0	0	0	0	0	0	1	1	1	1	2	2	2	2	2	2	1	1	1	0	0	0	0
5	Winter	Mon-Fri	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
6	Summer	Mon-Fri	0	0	0	0	0	1	1	1	1	1	2	2	2	2	2	2	2	1	1	1	1	0	0	0
6	Winter	Mon-Fri	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	2	2	2	1	1	0	0	0
7	Summer	Mon-Sat	0	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	2	0	0	0	0
7	Winter	Mon-Sat	0	0	0	0	0	0	0	0	0	0	0	2	2	2	2	2	2	2	2	0	0	0	0	0

In order to calculate customer bills for TOU tariffs, the billing period consumption needs to be distributed over the TOU periods; to use the period definitions illustrated in Table 7, we need hourly building electricity use. For this study we use an existing database of commercial building simulations that were initially developed for the DOE standards rule-making process [7]. The simulation database includes over one thousand buildings in several dozen weather locations, and a weight for each building corresponding to the number of similar buildings in the population. Here we use the hourly time series of total electricity use to to create a model that defines, for each TOU tariff, the percentage of billing period electricity use that is allocated to each TOU period.

For electricity consumption, the modeling steps are as follows:

1. Buildings and tariffs are aligned by census division; *e.g.* , if tariff i is defined for a state in census division 5, then only buildings in census division 5 are analyzed for this tariff.

2. For each tariff, each building eligible to be assigned to that tariff, and each month, we use the hour assignments illustrated in Table 7 to sum the electricity use in each TOU period.

Table 8: Fraction of time that the peak demand occurs in a given TOU period for different builidng types.

Building Type	Shoulder	Off-Peak	On-Peak
All	0.15	0.11	0.73
Fast Food Restaurant	0.25	0.08	0.67
Hospital	0.17	0.11	0.73
Large Office	0.15	0.10	0.74
Large Retail	0.16	0.13	0.70
School	0.24	0.12	0.64
Sit-down Restaurant	0.22	0.09	0.69
Small Office	0.13	0.11	0.75
Small Retail	0.15	0.12	0.72
Warehouse	0.16	0.08	0.76

3. For each tariff, building and month, the electricity use in a period is converted to a percentage of the total billing period electricity consumption allocated to that period.

4. For each tariff and building, we take a simple average over the months to get the allocation of electricity consumption by period for each season.

5. For each tariff and season, we average over the buildings assigned to that tariff to define a typical value for the percentage of electricity use allocated to each period. This calculation uses the building weights developed for the sample. We also define building-type-specific allocations by including only the appropriate building types in the average.

The process defines, for each tariff, the percent of energy use that occurs in the on-peak, off-peak, and shoulder periods (for summer and winter separately if appropriate). These percentages are then applied to the bill data to generate the necessary bill inputs. When the bill is decremented, we assume that the electricity savings is distributed across TOU periods in the same proportion as the baseline electricity consumption.

For the demand data, for each tariff we count how often the peak billing demand occurs in each TOU period, across all months in a season and all buildings in the appropriate set. The probability (across all tariffs) of the peak demand occurring in each period for each building type in the sample is provided in Table 8. In doing the bill calculations, we apply demand charges based on the most likely period for that tariff and building type. In calculating the marginal demand price, we assume that the period in which peak demand occurs is not affected by the demand reduction. If the building load shape is not too flat, and/or the magnitude of the energy savings is not too large, this assumption should be reasonable. A more precise assessment would require detailed building- and measure-specific data that are not available for this analysis.

Figure 7 illustrates the electricity use allocation for some of the TOU tariffs in the TAP data set. These are organized along the horizontal axis by region; the chart shows data for the summer season only. Each bar corresponds to one tariff. The percentages shown in the chart correspond to an average over all buildings. In the western states a little over 30% of electricity use is allocated to peak periods in the summer; in eastern regions this allocation is more variable and typically larger.

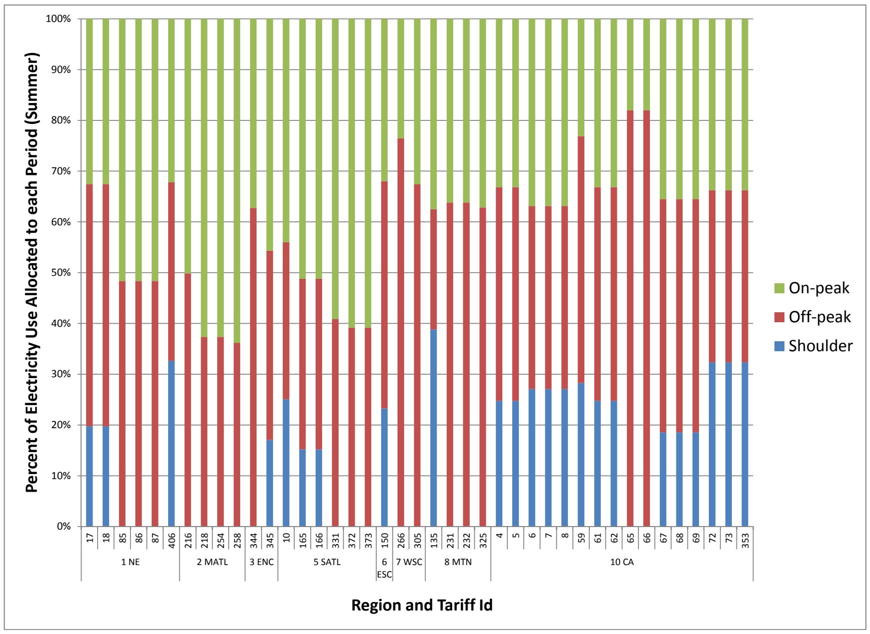

Figure 7: Distribution of billing period electricity use into TOU periods for a selection of TOU tariffs in TAP, for the summer season. The horizontal axis labels are the TAP internal tariff ID and the region code.

The percent of energy used in a given TOU period is different from the percent of hours that are assigned to that period. In on-peak periods, the percent of electricity consumed may be 30-90% larger than the percent of all hours that fall into that period. For off-peak periods, the percent of electricity consumed is 10-40% smaller than the percent of all hours that fall into the off-peak period. For example, if a tariff allocates 30% of hours to on-peak and the other 70% to off-peak, then energy use would be something like 50% in on-peak and 50% off-peak. This relationship varies by building; a useful way to visualize the variation is shown in Figure 8. This figure plots the percent of energy allocated to the peak period *vs.* the percent of hours allocated to the peak period, for the summer season, for three building types. The line $y = x$ is plotted for reference. Diamonds are for all building types averaged together, open squares for schools, and open triangles for fast food restaurants. The latter two building types were chosen for the plot because they show the largest deviation from the all-buildings average. Each point corresponds to a single tariff. The points for each building type line up vertically because, for a given tariff, the percent of hours allocated to on-peak doesn't depend on the building to which the tariff is applied. Schools have a higher proportion of electricity use in on-peak hours because they have less

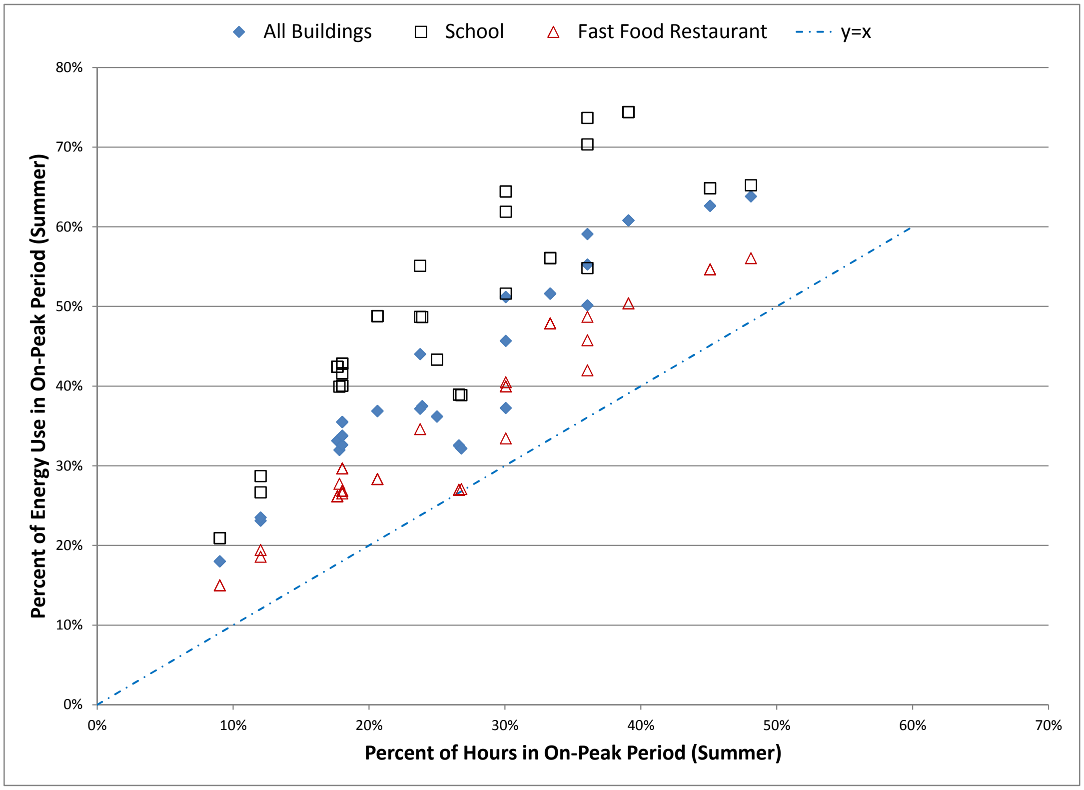

Figure 8: Scatter plot of the percent of energy allocated to the peak period *vs.* the percent of hours allocated to the peak period, for the summer season. The line $y = x$ is plotted for reference. Diamonds are for all building types averaged together, open squares for schools, and open triangles for fast food restaurants.

diverse schedules than general commercial buildings, typically open only week-days. Fast-food restaurants have a lower proportion of on-peak electricity use because more of their business activity occurs nights and weekends, which are usually off-peak.

The TOU prices included in the regional averages are based on the distribution patterns for all buildings averaged together, and assumes that the distribution of the energy decrement across TOU periods is the same as in the baseline. We have performed two sensitivity analyses to determine whether these assumptions affect the calculated prices. In the first test, we calculate marginal prices for TOU tariffs using the distribution of energy and demand for schools, and using those for fast-food restaurants, and compare these to the prices calculated using all buildings. We do not find any significant change in the marginal prices across these different building types. In the second test, we alter the distribution pattern of the energy decrement only. We look at two additional cases; one in which the energy decrement in each period is proportional to the number of hours allocated to that period (a flat decrement), and one in which the quantity of electricity allocated to the peak period is increased by 50% relative to the baseline proportions (a peaking decrement). In both cases there is little or no change to the marginal energy price. With regard to the demand price, the only significant impact of altering the distribution of the energy decrement is that, in a few cases, it shifts the peak demand period out of one period into another. This can result in a significant change to the demand charge. However, these shifts can be either positive or negative, *i.e.* in some cases the peak demand is shifted to a higher cost period and in others to a lower cost period. While this effect would be important in valuing energy savings in a detailed, building-level analysis, we do not believe it introduces any systematic bias into the marginal price estimates.

5 Comparison of EIA, TAP and EEI Prices

In this section we present results for each data set and compare them. The only quantity that can be compared across all three data sets is the annual average price, plotted in Figure 9, for each region and each bill group. For the EIA861 data, the average shown in the plot is based on the commercial revenues and sales for Group A, industrial revenues and sales for Group C, and the combined non-residential data for Group B. The three data sets agree reasonably well, with each capturing the same pattern of high *vs.* low prices by region. The EIA861 average prices are consistently lower than the EEI or TAP values, which is to be expected given the differences in the weighting procedure. The EIA numbers are based on an implicit consumption weighting across all customers irrespective of bill group, which assigns relatively more weight to the largest customers who have the lowest prices. With regard to the TAP and EEI data, TAP values are higher in some regions and bill groups and lower in others, demonstrating that there is no systematic bias in one data set *vs.* the other. Differences due to sampling and calculation methods between these two data sets are discussed further below.

Tables of marginal electricity consumption and demand prices, and average prices, by bill group, for the TAP and EEI data are presented in the Appendix. As noted in the introduction, the EMP provides a more direct measure of potential bill savings associated with an energy savings measure. To illustrate the behavior of this metric, we present in Figures 10 and 11 curves of the EMP as a function of the variable MLF, based on EEI data, for a selection of regions and years. Each of the four bill groups is plotted for the years 2007, 2010, 2014 and 2017, for five regions. The scale of the MLF is reversed so that it decreases going to the right, with the lower bound in the plots set equal to 0.2. Low values of MLF correspond to a strongly peaked shape for the load reduction, and high values to relatively flat shape. In general these curves are fairly flat up to a MLF of about 0.4, and begin to rise steeply as the MLF decreases below that. The steepness of the rise can be thought of as a measure of the value placed on the capacity component of the cost of service. The EMP can increase by a factor of 2-4 moving across the curve, confirming that the MLF is an important factor to consider in estimating the marginal value of changes to electricity use. The curves also provide a sense of the way prices have evolved over the last 10 years. In most regions the curves have retained the same shape, but shift up and down in the plane. Prices have generally risen over time, with the notable

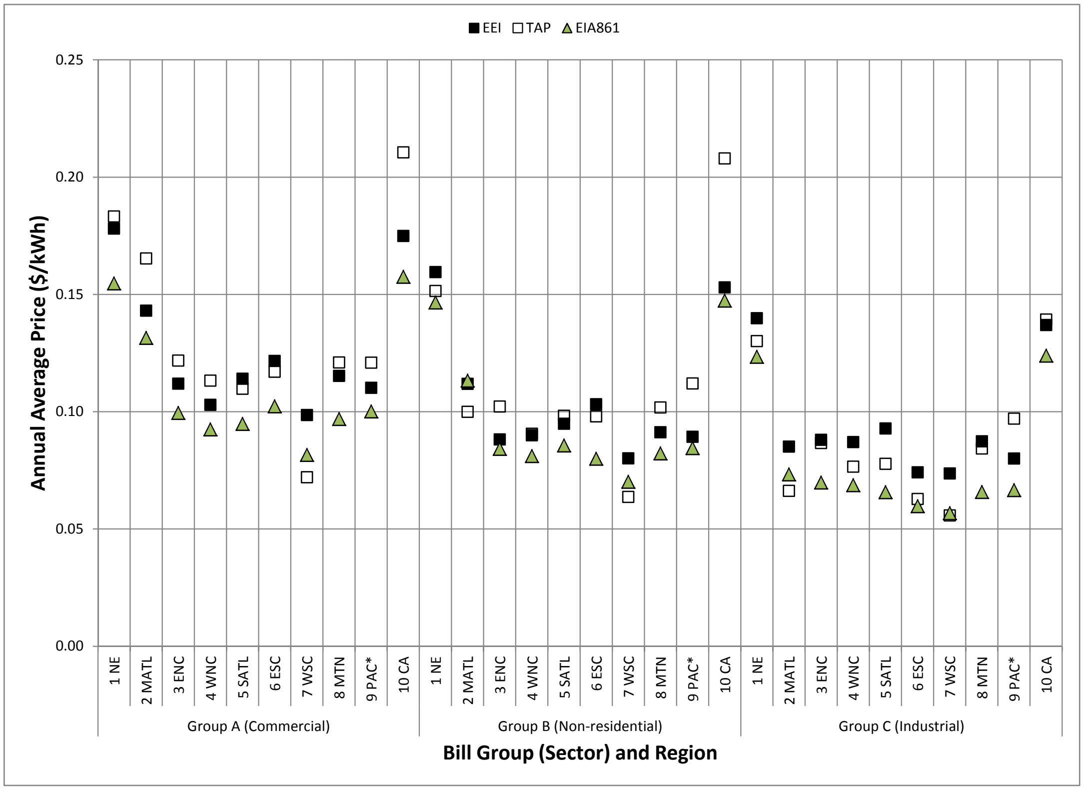

Figure 9: Annual average prices for the TAP (open squares), EEI (filled squares) and EIA861 (green triangles) data by region, all for 2015, by bill group and region. For the EIA861 data, the average shown in the plot is based on the commercial revenues and sales for Group A, industrial revenues and sales for Group C, and the combined non-residential data for Group B.

exception of the Mid-Atlantic region in which the cost of electricity in groups B and C has decreased substantially since 2010. Some regions show a change in the shape of the curve with time, which indicates a change in the relative importance of commodity *vs.* capacity components to the marginal cost of service. This figure is meant to be illustrative; Tables 13 and 12 in the Appendix provide the underlying data for all regions.

Price comparisons between TAP and EEI for 2015 are presented for each bill group in Figures 12, 13, and 14. These figures show three metrics with units of $/kWh: the EMP calculated for MLF=0.5, the marginal energy price, and the average price. To make the figure more legible, the data are plotted on two axes; one for summer (red, left-hand axis) and one for winter (blue, right-hand axis). Both axes use the same scale and units. EEI data are shown as filled squares, and TAP data as open squares. The average prices calculated from the two data sets generally agree well, and show the same pattern of regional variation. For the bill groups B and C (corresponding to demand greater than 100

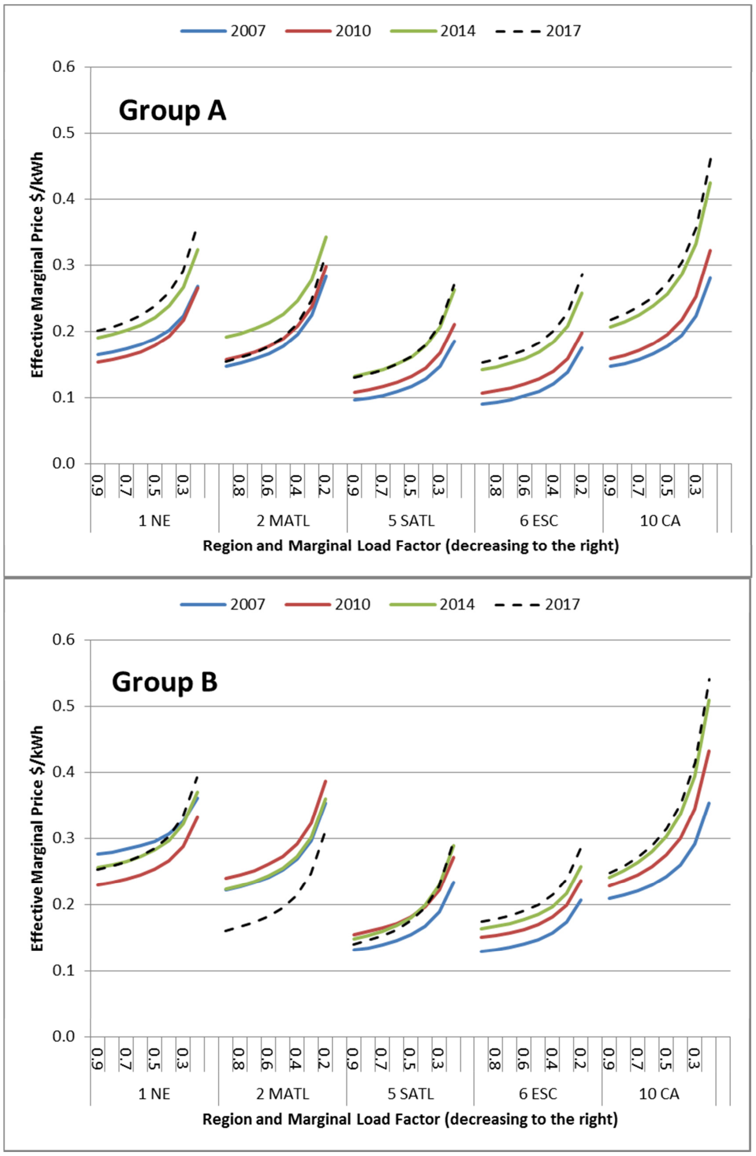

Figure 10: Curves of the EMP as a function of the MLF based on EEI data for bill groups A and B. Curves are shown for a selection or regions for the years 2007, 2010, 2014 and 2017. Curves are color-coded by year.

kW) the marginal energy price and EMP also agree well. Because the EMP incorporates the demand effect, this implies that the demand charges are consistent between EEI and

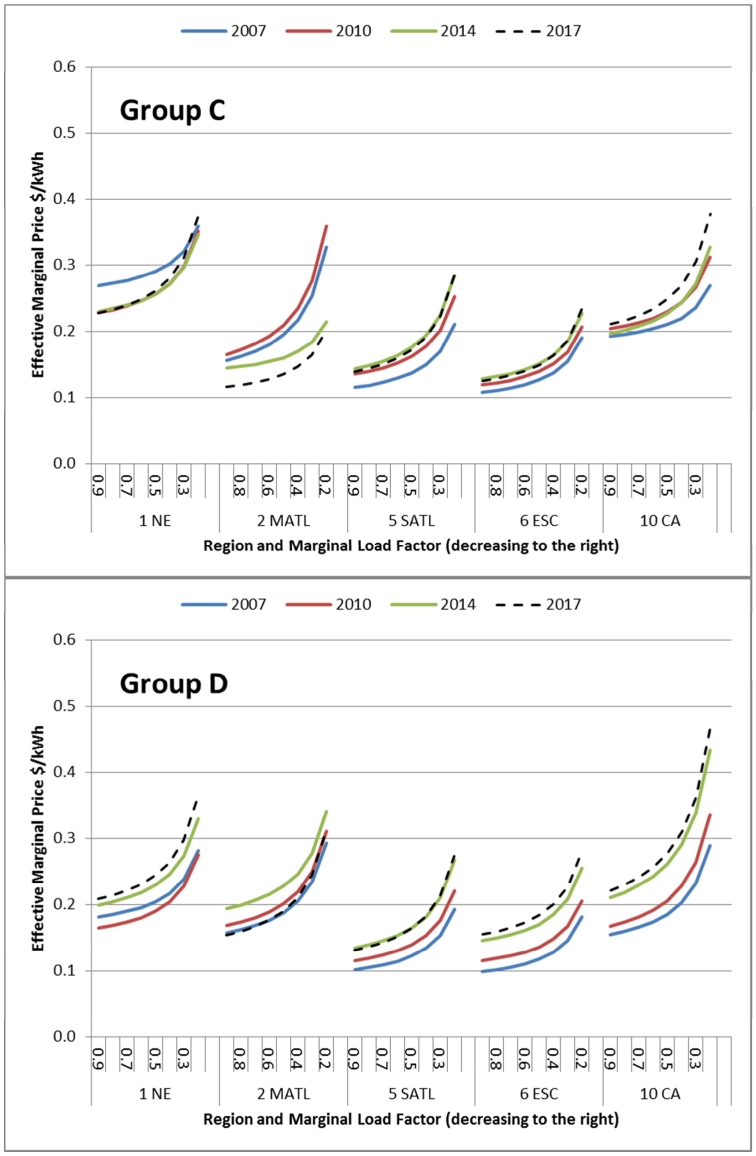

Figure 11: Curves of the EMP as a function of the MLF based on EEI data for bill groups C and D. Curves are shown for a selection or regions for the years 2007, 2010, 2014 and 2017. Curves are color-coded by year.

TAP for the higher kW bills. Group A shows the largest discrepancy between EEI and TAP, with the marginal energy price generally lower for the EEI data than for the TAP

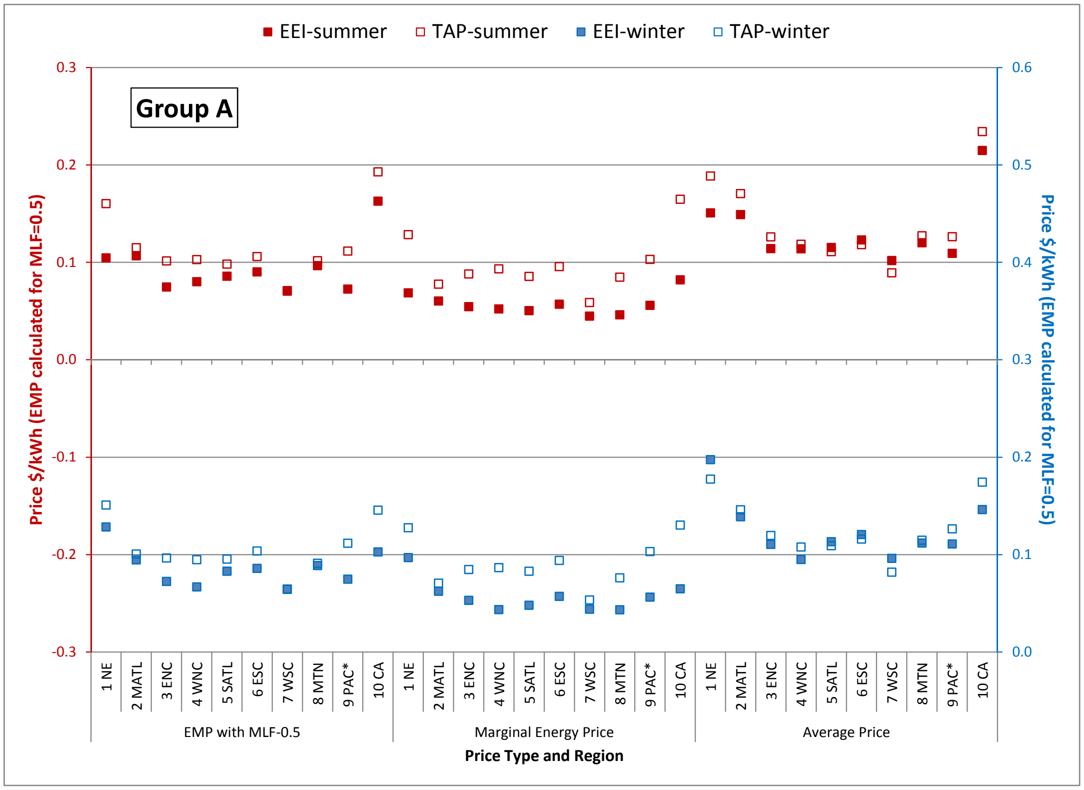

Figure 12: Comparison of prices calculated with EEI and TAP for Group A. The plot shows the EMP calculated for MLF=0.5, the marginal energy price, and the average price. The data are plotted on two axes; one for summer (red, left-hand axis) and one for winter (blue, right-hand axis). EEI data are shown as filled squares, and TAP data as open squares.

data. Review of Tables 10 and 11 in the appendix shows that there is considerable variation within Group A, particularly for the very small demand range (less than 20kW). This means that the results for Group A are averaged over greater variability than the other bill groups, so it is not surprising that the two data sets show larger differences. We note that the TAP and EEI values of the EMP are in better agreement than the marginal energy price, so differences in the marginal energy and marginal demand prices between the two data sets offset one another to some extent.

There are several ways in which the TAP and EEI samples and methods differ. One is that the bill group averages for TAP include the full set of 32 bills, with marginal and average prices available for all bill values. In contrast, there are only 15 EEI bills and, due to methodological limitations, marginal prices can only be calculated for a few of these. To test the importance of the extra TAP bills, we recalculated the TAP regional and bill group averages, but used only those bills that also appear in the EEI data set (with appropriate

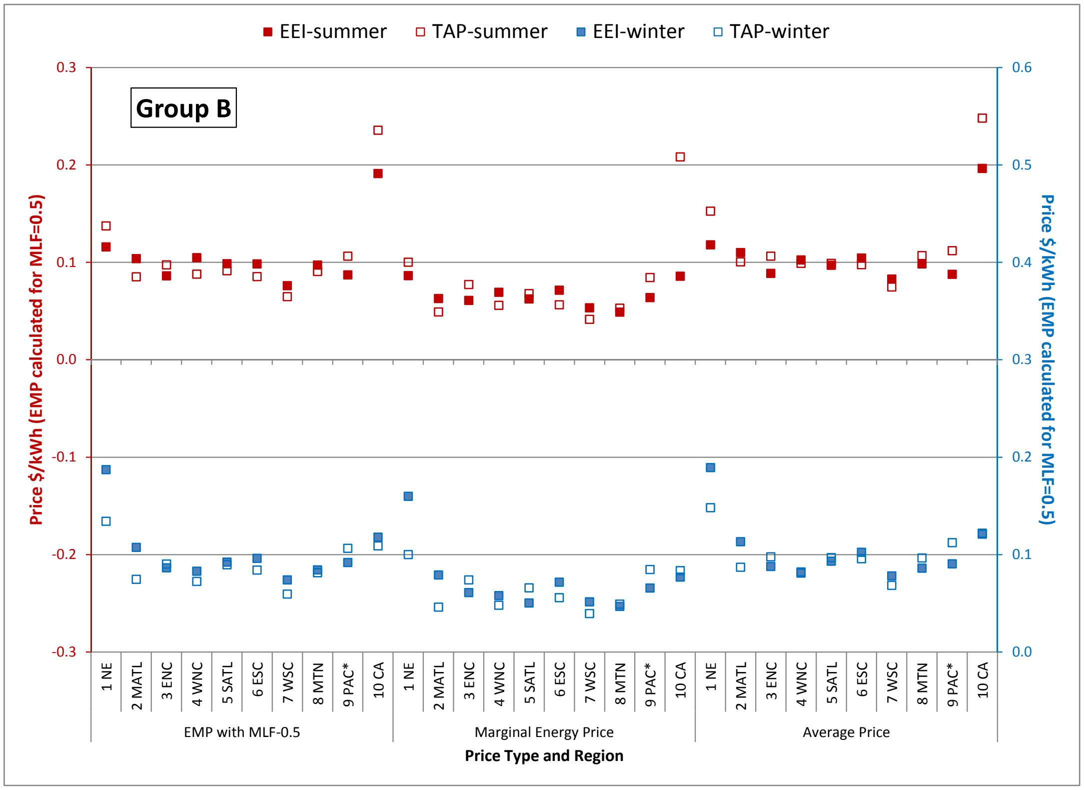

Figure 13: Comparison of prices calculated with EEI and TAP for Group B. The plot shows the EMP calculated for MLF=0.5, the marginal energy price, and the average price. The data are plotted on two axes; one for summer (red, left-hand axis) and one for winter (blue, right-hand axis). EEI data are shown as filled squares, and TAP data as open squares.

adjustment of the weights). This calculation results in change to the EMP that is generally less than ±4% (across bill groups and regions), and is not systematic in sign.

A second difference between the two data sets is that TAP contains fewer utilities than the EEI sample. The total commercial and industrial sales covered by the TAP and EEI samples (based on EIA861 data for 2015) are tabulated in Table 9. The differences in coverage vary by region; in some regions the TAP data cover slightly more sales than EEI due to included POUs. To test the effect of this difference on prices, we revised the calculation of EEI prices (using the EMP at MLF=0.5 as representative) to include only those utilities that are also in TAP. Comparing these to EEI prices calculated with the full EEI sample, we find again that in most regions the effect is on the order of a few percent. It is mostly positive, meaning that restricting the EEI average to the TAP utilities raises the calculated price and therefore can explain some of the difference seen in the two data sets. In regions 2 (NE) and 9 (PAC*) differences are on the order of 10%.

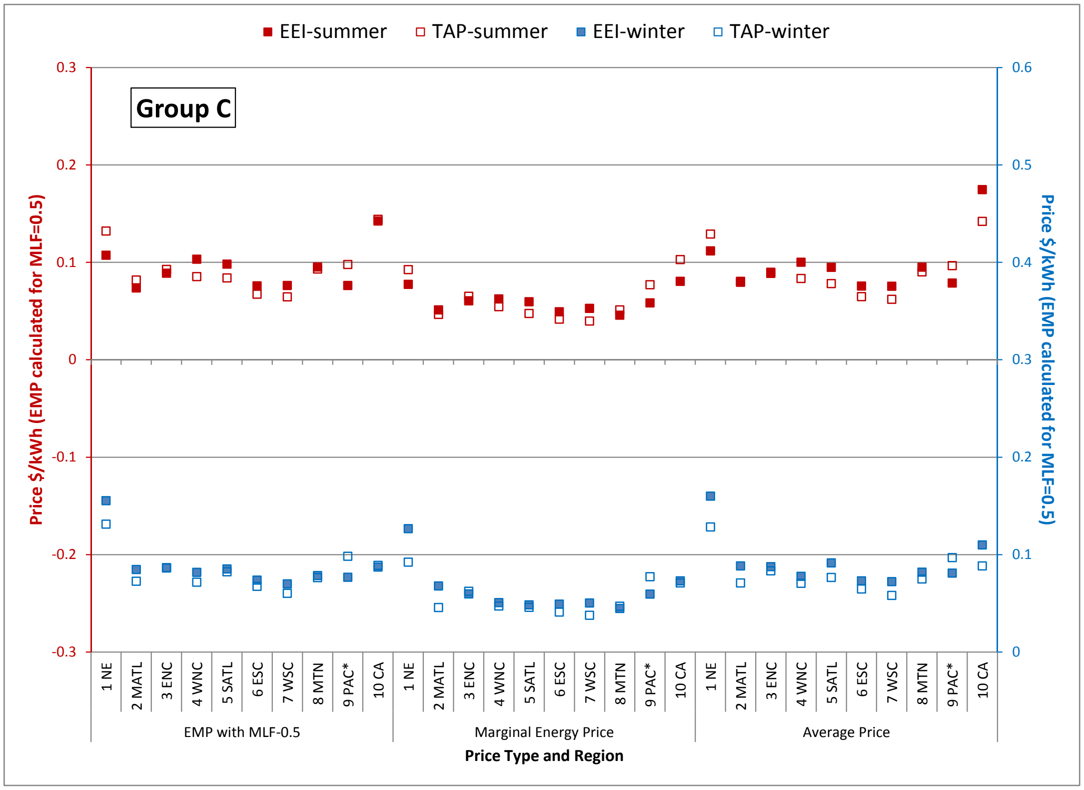

Figure 14: Comparison of prices calculated with EEI and TAP for Group C. The plot shows the EMP calculated for MLF=0.5, the marginal energy price, and the average price. The data are plotted on two axes; one for summer (red, left-hand axis) and one for winter (blue, right-hand axis). EEI data are shown as filled squares, and TAP data as open squares.

A third source of discrepancy between the two data sets is in the method we use to correct for under-representation of POUs. For the EEI data, we applied a correction factor calculated from the EIA861 sample, which represents an average effect across all utilities in a region. For the TAP data, we re-weighted the POU utilities in each region, typically increasing their weight to represent the full portion of POU-supplied service. Because specific utilities may or may not have demand charges, and/or the demand charges may apply in only one season, this approach leads to different magnitudes of correction factor by season and by price type. To estimate the impact of the re-weighting used in TAP, we have calculated the equivalent of the adjustment factor that is implicit in the TAP methodology. This is defined as the ratio of the price calculated for the full TAP sample to the price calculated only for the IOUs in the TAP sample. This factor is plotted in Figure15. In the figure, the striped bars show the calculated factor for the marginal energy charge, and the solid blue bars are for the marginal demand charge. The adjustment

Table 9: Total commercial and industrial retail sales in MWh for 2015, for utilities included in the TAP and in the EEI samples. The table also shows the ratio of the sales covered in TAP to the sales covered in EEI.

	Commercial Sales			Industrial Sales		
Region	EEI	TAP	TAP:EEI	EEI	TAP	TAP:EEI
1 NE	12,842	13,282	1.03	2,308	2,371	1.03
2 MATL	37,154	28,479	0.77	4,340	2,158	0.50
3 ENC	88,717	50,381	0.57	84,421	35,568	0.42
4 WNC	65,793	37,681	0.57	52,195	31,507	0.60
5 SATL	221,452	197,334	0.89	100,241	72,478	0.72
6 ESC	36,357	19,703	0.54	44,768	30,264	0.68
7 WSC	59,140	42,632	0.72	71,029	58,676	0.83
8 MTN	63,181	45,094	0.71	52,441	33,154	0.63
9 PAC*	28,027	8,098	0.29	13,027	6,009	0.46
10 CA	72,273	72,035	1.00	27,400	27,250	0.99

factors calculated from EIA (applied to the EEI data) are shown as black bars for comparison. The chart shows again that the magnitude of the effect is regionally variable, but it is clear that the re-weighting used in TAP leads to significantly different adjustments for demand *vs.* energy prices. This can also be a contributing factor to the differences between prices calculated with TAP and those calculated with EEI.

6 Conclusions

In this paper we have provided a comprehensive review of data and methods to calculate electricity prices for the non-residential sector. Tariffs for non-residential consumers can be very complex, and vary greatly from one utility to another. Here we have used the consumer bill as the starting point for the data analysis, examining in detail how the bill changes as a function of the billing period electricity demand and consumption. We have shown that changes to the bill can be represented using the effective marginal price (EMP), which is a function of the marginal load factor (MLF). The EMP includes two components: the marginal energy price and the marginal demand price. The EMP is defined so that it can be used, for example in cost-benefit analysis, in the same way as a simple commodity price for electricity. Incorporation of the MLF into the expression for the EMP allows demand charges to be accounted for correctly.

We have reviewed three data sources: EIA Form 861 annual and monthly, EEI Typical Bills reports, and the TAP tariff data compiled and analyzed at LBNL for 2015. Each data set has strengths and weaknesses:

- the EIA data provide complete coverage of the utility industry but can only be used to calculate average prices;
- the EEI data sample only IOUs; while they do provide sufficient information to calculate average, marginal energy, and marginal demand prices, the EEI sample only

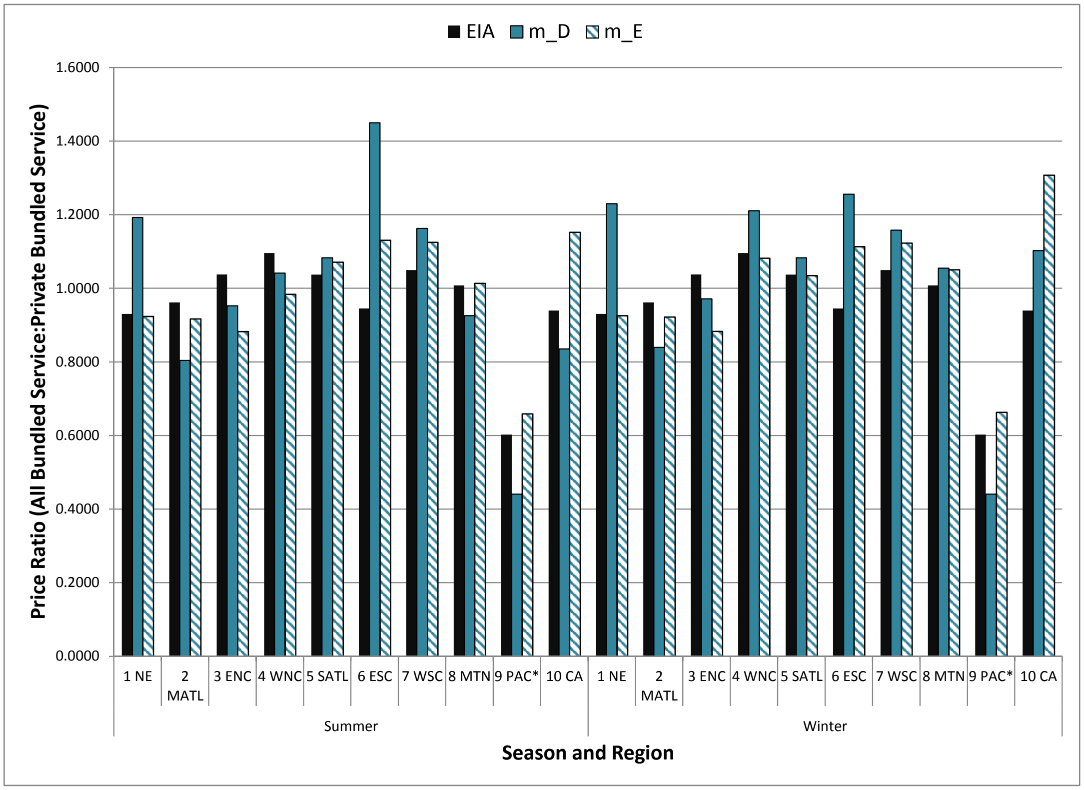

Figure 15: The plot compares the effect of using two different approaches to correct the TAP and EEI data for non-sampling of POUs. The implicit adjustment factor for TAP is defined as ratio of the price calculated for the full TAP sample to the price calculated only for the IOUs in the TAP sample. The implicit factor is plotted by region and season for the TAP marginal energy prices (solid blue bars), TAP marginal demand prices (striped blue bars), and compared to the EIA-based adjustment factor (solid black bars).

includes a small number of customer sizes (as defined by peak load) and load factors;

- the TAP data provide detailed information about tariffs, and are the only data set that allow prices to be calculated without approximation for any bill input; given the complexity of non-residential tariffs, the TAP sample is relatively small and data are updated infrequently.

All three data sets provide both seasonal and regional information, and we have found that there is significant variation in prices with these variables. Our price estimates are presented for summer, winter and annual periods, and use 10 regions (based on census divisions, with California broken out separately). Our review of the EIA861 data has shown that there are significant differences in average prices by utility provider and service type. As both TAP and EEI cover bundled service only, and under-sample the POU sector, we have developed a methodology to adjust for any potential sampling bias.

For practical use, we want to develop a set of prices that are applicable to the non-residential sector in general. This in turn requires information on how billing period energy and demand values are distributed over the population of commercial and industrial consumers. Here we have used the EIA's CBECS survey to provide this information. Sample weights associated with individual CBECS bills have been converted to a frequency distribution, which is a function of the log of demand and the load factor, as shown in Figure 1. From this distribution, we have defined a set of representative values of demand and load factor, as those that appear most frequently in the data. These representative bill input values are further aggregated into three billing groups: Group A (demand < 100 kW), Group B (demand between 100 and 1,000 kW), and Group C (demand > 1,000 kW). Sensitivity analyses using the TAP data confirm that prices are relatively homogeneous within groups A, B and C; all prices are reported separately for each group. We also define a Group D, which represents the full non-residential population. Data tables in the Appendix provide prices by billing group, region and season.

Many utilities require non-residential consumers to take service on TOU tariffs, which introduces an additional complicating factor, as the calculated prices may depend on the distribution of energy use across TOU periods. We have created a model, based on hourly building load data obtained from a simulation database, that provides factors to allocate billing period energy use and demand to each TOU period, and conducted sensitivity analyses to determine how prices vary when this allocation is changed. In general we find that prices are insensitive to the details of how energy use is distributed across TOU periods.

The marginal prices calculated with TAP and EEI are compared across bill groups in Figures 12, 13 and 14. Overall the two data sources agree well, particularly for the larger demand bill groups (B and C). Within group A, the TAP data tend to show higher marginal energy prices, but these are offset to a certain extent by lower marginal demand prices. Hence, the EMP is more consistent between the two data sets than the component marginal prices. We have shown that discrepancies in prices calculated using the TAP and EEI data are due primarily to the fact that the two data sets have different structures, and require slightly different analysis methods.

We consider the EEI data as the most practical source for developing non-residential electricity prices, for a number of reasons. The EEI sample, although limited to IOUs, is more complete than TAP. EEI data are published each year for both summer and winter, whereas TAP is updated infrequently. The method we use to correct for under-sampling POUs in TAP leads to some inconsistencies between the different price types, and it is likely that the adjustment method developed for EEI data is more reliable.

The biggest limitations with the EEI data are that (1) they provide limited coverage of the wide range of bills commonly seen in the non-residential sector, and (2) marginal prices can only be calculated approximately. The TAP data have been invaluable in confirming that the approximations necessary to the EEI analysis do not lead to significant under- or over-estimation of prices. The TAP data are most useful when detailed building or facility load data are also available; the variability demonstrated within the TAP tariffs demonstrates the importance of considering specific pricing schemes when valuing energy savings or load management measures at a single location. A future goal of the TAP work is to couple this database to building-level energy analysis platforms, and so improve the precision of the energy savings valuations generated by these tools.

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A Detailed Tables

A.1 TAP Bill Results

Tables 10 and 11 provide results of the bill calculations using TAP. Table 10 shows the marginal demand price, and Table 11 the marginal energy price, for summer and winter. In these tables the bills are arranged in the order of increasing demand, and color coding is used to indicate the price magnitudes. The table shows that the marginal price is frequently constant over a range of bills, or equivalently, demand and consumption values. To simplify the presentation of results, we have defined 3 bill groups based on these general trends in the data. The bill groups are labeled A, B and C in the table, and correspond to three demand ranges (the bill group is also listed in Table 3). Group A contains bills with demand less than 100 kW, Group B contains bills with demand between 100 kW and 1000 kW, and Group C bills with demand larger than 1000 kW. While there is a substantial amount of variability within Group A, higher demand charges are often offset by lower energy charges and vice versa, resulting in less variability in the EMP.

Tables 12 and 13 summarize results of the TAP and EEI analyses by bill group, region and season. Table 12 shows the annual and seasonal marginal prices and average prices for TAP, and Table 12 shows the same data for EEI. The marginal energy and demand prices shown in the tables can be used, along with equation (10) to calculate the EMP.

Table 10: Seasonal marginal demand price estimates for all TAP bills. The data are color-coded so that low values appear blue and high values appear red. Values for each bill are shown, with the ordering as in Table 3.

Bill Group	Index	Summer Marginal Demand Charge $/kW 1 NE	2 MATL	3 ENC	4 WNC	5 SATL	6 ESC	7 WSC	8 MTN	9 PAC*	10 CA
A	1	2.54	5.65	1.43	1.30	0.59	0.03	0.00	0.00	0.00	1.49
A	2	2.54	5.65	1.43	1.30	3.79	0.03	0.00	0.00	0.00	1.49
A	3	10.98	14.49	4.60	2.72	0.23	0.03	2.68	0.38	0.00	1.49
A	4	11.19	14.49	4.60	2.92	4.02	0.03	3.64	0.38	0.00	1.49
A	5	11.19	14.45	4.60	3.06	4.18	0.03	3.64	1.00	0.00	1.49
A	6	12.67	14.45	4.69	3.46	6.25	2.80	6.75	4.94	3.97	16.90
A	7	12.67	14.45	4.69	3.46	6.34	2.80	6.75	5.30	3.97	16.90
A	8	12.35	14.83	5.00	3.48	3.41	1.47	4.27	9.93	4.88	18.27
A	9	12.56	14.79	5.00	3.69	6.61	2.88	6.21	10.93	5.79	17.65
A	10	13.32	14.79	5.00	3.83	6.64	3.01	6.55	10.93	5.79	17.65
A	11	12.85	14.79	5.88	3.68	4.50	10.56	4.51	12.61	5.68	18.27
A	12	15.97	14.79	6.83	5.91	7.57	12.15	6.85	12.61	6.52	17.82
A	13	13.82	14.79	6.08	4.19	7.30	10.61	6.54	12.61	6.52	17.65
A	14	15.97	14.79	7.03	6.12	7.61	12.11	6.93	12.61	6.52	17.82
A	15	15.97	14.79	7.03	6.12	7.72	12.11	6.93	12.61	6.52	17.82
B	16	13.17	13.20	7.45	9.75	5.86	10.11	7.90	13.20	7.15	9.67
B	17	13.17	13.20	7.45	10.60	8.72	10.18	8.13	13.20	7.15	9.67
B	18	13.84	13.20	7.45	12.53	8.72	11.80	8.30	13.20	7.15	9.67
B	19	13.84	13.24	7.45	12.14	9.16	10.23	9.29	14.09	8.99	10.44
B	20	13.84	13.24	7.45	12.14	9.29	10.23	9.29	14.09	8.99	10.44
B	21	13.75	13.24	7.48	11.21	8.75	10.23	8.13	15.35	8.97	10.44
B	22	13.75	13.24	7.48	13.03	8.75	10.23	8.30	15.35	8.97	10.44
C	23	13.78	12.77	7.51	10.47	12.62	8.17	7.85	14.81	7.64	15.58
C	24	14.64	12.77	7.51	11.14	13.15	9.92	8.09	14.81	7.64	15.58
C	25	14.64	12.77	7.62	11.14	13.53	9.92	9.15	14.81	7.64	15.58
C	26	14.64	13.05	12.55	11.88	13.76	10.36	9.19	15.82	7.55	14.66
C	27	14.62	13.05	13.14	11.07	14.00	10.19	11.40	16.08	7.58	14.66
C	28	14.62	13.05	12.93	11.78	13.10	10.07	11.16	16.08	7.58	14.66
C	29	14.62	13.05	13.14	11.80	13.62	10.19	11.40	16.08	7.58	14.66
C	30	14.62	13.05	13.58	10.48	13.02		11.64	17.27	7.58	14.66
C	31	14.62	13.05	13.72	11.80	13.45		11.88	17.27	7.58	14.66
C	32	14.62	13.05	13.72	11.80	13.83		11.88	17.27	7.58	14.66

Bill Group	Index	Winter Marginal Demand Charge $/kW 1 NE	2 MATL	3 ENC	4 WNC	5 SATL	6 ESC	7 WSC	8 MTN	9 PAC*	10 CA
A	1	2.54	4.12	1.32	1.30	0.59	0.03	0.00	0.00	0.00	1.49
A	2	2.54	4.12	1.32	1.30	3.79	0.03	0.00	0.00	0.00	1.49
A	3	7.51	11.51	4.12	2.46	0.23	0.03	2.36	0.35	0.00	1.49
A	4	7.72	11.51	4.12	2.51	4.02	0.03	3.32	0.35	0.00	1.49
A	5	7.72	11.52	4.12	2.65	4.16	0.03	3.32	0.97	0.00	1.49
A	6	9.15	11.52	4.21	2.83	6.24	2.80	5.87	4.82	3.97	8.07
A	7	9.15	11.52	4.21	2.83	6.32	2.80	5.87	5.18	3.97	8.07
A	8	8.83	11.88	4.49	3.01	3.41	1.47	3.70	8.59	4.88	9.69
A	9	9.05	11.88	4.49	3.07	6.59	2.88	5.70	9.58	5.79	9.02
A	10	9.80	11.88	4.49	3.21	6.62	3.01	5.86	9.58	5.79	9.02
A	11	9.33	11.88	5.37	3.18	4.49	9.93	3.93	11.24	5.68	9.69
A	12	12.45	11.89	5.48	4.97	7.55	11.52	6.16	11.24	6.52	9.19
A	13	10.30	11.88	5.55	3.45	7.28	9.98	5.83	11.24	6.52	9.02
A	14	12.45	11.89	5.66	5.14	7.59	11.48	6.05	11.24	6.52	9.19
A	15	12.45	11.89	5.66	5.14	7.70	11.48	6.05	11.24	6.52	9.19
B	16	12.02	10.45	5.98	8.01	5.84	9.53	6.85	11.83	7.15	9.22
B	17	12.02	10.45	5.98	8.58	8.70	9.59	7.01	11.83	7.15	9.22
B	18	12.69	10.45	5.98	9.42	8.70	11.22	7.09	11.83	7.15	9.22
B	19	12.69	10.49	5.98	9.02	9.14	10.54	8.08	11.31	8.99	9.47
B	20	12.69	10.49	5.98	9.02	9.28	10.54	8.08	11.31	8.99	9.47
B	21	12.63	10.49	6.01	9.19	8.73	10.54	7.01	12.58	8.97	9.47
B	22	12.63	10.49	6.01	9.91	8.73	10.54	7.09	12.58	8.97	9.47
C	23	13.55	9.77	5.94	8.83	12.62	8.51	7.03	11.39	7.64	6.54
C	24	14.41	9.77	5.94	8.69	13.15	10.25	7.27	11.39	7.64	6.54
C	25	14.41	9.77	6.00	8.69	13.53	10.25	8.34	11.39	7.64	6.54
C	26	14.41	10.03	11.44	9.41	13.76	10.69	8.36	9.78	7.55	6.70
C	27	14.38	10.03	11.94	8.61	14.00	10.19	10.39	10.05	7.58	6.70
C	28	14.38	10.03	11.82	9.31	13.09	10.07	10.15	10.05	7.58	6.70
C	29	14.38	10.03	11.94	9.33	13.62	10.19	10.39	10.05	7.58	6.70
C	30	14.38	10.03	12.12	8.79	13.02		10.63	10.54	7.58	6.70
C	31	14.38	10.03	12.23	9.33	13.45		10.87	10.54	7.58	6.70
C	32	14.38	10.03	12.23	9.33	13.83		10.87	10.54	7.58	6.70

Table 11: Seasonal marginal electricity consumption price estimates for all TAP bills. The data are color-coded so that low values appear blue and high values appear red. Values for each bill are shown, with the ordering as in Table 3.

Bill		Summer Marginal Energy Consumption Charge $/kWh										Winter Marginal Energy Consumption Charge $/kWh									
Group	Index	1 NE	2 MATL	3 ENC	4 WNC	5 SATL	6 ESC	7 WSC	8 MTN	9 PAC*	10 CA	1 NE	2 MATL	3 ENC	4 WNC	5 SATL	6 ESC	7 WSC	8 MTN	9 PAC*	10 CA
A	1	0.155	0.110	0.101	0.101	0.105	0.109	0.083	0.113	0.122	0.188	0.151	0.099	0.097	0.085	0.105	0.106	0.077	0.100	0.122	0.148
A	2	0.150	0.107	0.101	0.101	0.085	0.109	0.085	0.114	0.122	0.188	0.146	0.096	0.097	0.095	0.081	0.106	0.068	0.101	0.122	0.148
A	3	0.135	0.079	0.090	0.098	0.103	0.109	0.075	0.114	0.122	0.188	0.134	0.072	0.087	0.081	0.103	0.106	0.073	0.101	0.122	0.148
A	4	0.133	0.075	0.089	0.096	0.083	0.109	0.059	0.102	0.122	0.188	0.133	0.069	0.085	0.090	0.078	0.106	0.056	0.089	0.122	0.148
A	5	0.133	0.075	0.088	0.096	0.082	0.109	0.059	0.101	0.116	0.188	0.133	0.069	0.085	0.090	0.077	0.106	0.056	0.089	0.116	0.148
A	6	0.124	0.075	0.089	0.094	0.077	0.092	0.046	0.088	0.081	0.138	0.124	0.069	0.085	0.089	0.072	0.090	0.042	0.076	0.081	0.109
A	7	0.124	0.075	0.088	0.094	0.076	0.092	0.046	0.086	0.081	0.138	0.124	0.069	0.085	0.089	0.072	0.090	0.042	0.075	0.081	0.109
A	8	0.128	0.072	0.089	0.093	0.098	0.097	0.063	0.067	0.073	0.149	0.128	0.066	0.085	0.088	0.096	0.096	0.058	0.063	0.073	0.119
A	9	0.130	0.072	0.089	0.092	0.077	0.097	0.047	0.066	0.100	0.145	0.130	0.066	0.085	0.087	0.075	0.096	0.039	0.061	0.100	0.115
A	10	0.121	0.072	0.088	0.091	0.077	0.091	0.047	0.066	0.099	0.145	0.121	0.066	0.085	0.087	0.075	0.090	0.039	0.061	0.100	0.115
A	11	0.127	0.072	0.084	0.092	0.089	0.092	0.062	0.061	0.066	0.149	0.127	0.066	0.081	0.087	0.087	0.091	0.057	0.057	0.067	0.119
A	12	0.108	0.072	0.080	0.083	0.072	0.058	0.045	0.061	0.093	0.144	0.108	0.066	0.077	0.082	0.071	0.058	0.038	0.056	0.093	0.114
A	13	0.120	0.072	0.083	0.090	0.085	0.092	0.047	0.061	0.093	0.145	0.120	0.066	0.080	0.085	0.083	0.090	0.042	0.057	0.094	0.115
A	14	0.108	0.072	0.080	0.082	0.073	0.058	0.044	0.061	0.093	0.144	0.108	0.066	0.076	0.081	0.072	0.058	0.041	0.056	0.093	0.114
A	15	0.108	0.072	0.079	0.082	0.072	0.058	0.042	0.061	0.093	0.144	0.108	0.066	0.076	0.081	0.071	0.058	0.039	0.056	0.093	0.114
B	16	0.102	0.049	0.078	0.064	0.082	0.065	0.046	0.053	0.088	0.207	0.102	0.046	0.075	0.052	0.080	0.064	0.043	0.050	0.088	0.084
B	17	0.102	0.049	0.077	0.058	0.067	0.064	0.042	0.053	0.086	0.207	0.102	0.046	0.074	0.049	0.065	0.063	0.040	0.050	0.086	0.084
B	18	0.099	0.049	0.077	0.053	0.067	0.057	0.042	0.053	0.086	0.207	0.099	0.046	0.074	0.046	0.065	0.057	0.040	0.050	0.086	0.084
B	19	0.099	0.049	0.077	0.055	0.066	0.051	0.039	0.053	0.082	0.209	0.099	0.046	0.074	0.048	0.064	0.050	0.037	0.049	0.083	0.083
B	20	0.099	0.049	0.077	0.055	0.066	0.051	0.039	0.053	0.082	0.209	0.099	0.046	0.074	0.048	0.064	0.050	0.037	0.049	0.083	0.083
B	21	0.101	0.049	0.077	0.058	0.067	0.051	0.042	0.052	0.082	0.209	0.101	0.046	0.074	0.048	0.065	0.050	0.040	0.047	0.083	0.083
B	22	0.101	0.049	0.077	0.053	0.067	0.051	0.042	0.052	0.082	0.209	0.101	0.046	0.074	0.046	0.065	0.050	0.040	0.047	0.083	0.083
C	23	0.095	0.047	0.074	0.057	0.069	0.055	0.044	0.051	0.077	0.104	0.095	0.046	0.071	0.048	0.068	0.054	0.042	0.048	0.078	0.072
C	24	0.092	0.047	0.074	0.053	0.047	0.048	0.044	0.051	0.077	0.104	0.092	0.046	0.071	0.046	0.046	0.047	0.042	0.048	0.078	0.072
C	25	0.092	0.047	0.073	0.055	0.046	0.048	0.040	0.051	0.077	0.104	0.092	0.046	0.070	0.048	0.044	0.047	0.038	0.048	0.078	0.072
C	26	0.092	0.046	0.057	0.054	0.042	0.036	0.040	0.051	0.077	0.101	0.092	0.045	0.054	0.047	0.040	0.036	0.038	0.047	0.077	0.070
C	27	0.092	0.046	0.054	0.055	0.040	0.037	0.030	0.050	0.077	0.101	0.092	0.045	0.051	0.048	0.039	0.037	0.028	0.047	0.077	0.070
C	28	0.092	0.046	0.054	0.054	0.042	0.037	0.031	0.050	0.077	0.101	0.092	0.045	0.052	0.047	0.041	0.037	0.029	0.047	0.077	0.070
C	29	0.092	0.046	0.054	0.054	0.041	0.037	0.030	0.050	0.077	0.101	0.092	0.045	0.051	0.047	0.039	0.037	0.028	0.047	0.077	0.070
C	30	0.092	0.046	0.056	0.058	0.042		0.029	0.050	0.075	0.101	0.092	0.045	0.052	0.049	0.041		0.027	0.047	0.075	0.070
C	31	0.092	0.046	0.055	0.054	0.041		0.028	0.050	0.075	0.101	0.092	0.045	0.051	0.047	0.039		0.026	0.047	0.075	0.070
C	32	0.092	0.046	0.055	0.054	0.040		0.028	0.050	0.075	0.101	0.092	0.045	0.051	0.047	0.039		0.026	0.047	0.075	0.070

Table 12: Annual and seasonal marginal electricity demand and consumption prices, and average prices, by bill group for the TAP data.

TAP Data 2015		Marginal Demand $/kW				Marginal Energy $/kWh				Average $/kWh			
Season	CD/LS	A < 100	B 100-1000	C > 1000	D All Bills	A < 100	B 100-1000	C > 1000	D All Bills	A < 100	B 100-1000	C > 1000	D All Bills
Annual	0 USA	5.63	9.23	10.37	6.41	0.0875	0.0648	0.0518	0.0823	0.1255	0.1002	0.0773	0.1192
	1 NE	10.08	13.05	14.40	10.55	0.1281	0.1001	0.0924	0.1237	0.1831	0.1504	0.1287	0.1777
	2 MATL	12.34	11.84	11.40	12.25	0.0741	0.0476	0.0461	0.0698	0.1584	0.0938	0.0753	0.1474
	3 ENC	4.58	6.72	9.40	5.26	0.0864	0.0756	0.0638	0.0831	0.1230	0.1020	0.0865	0.1170
	4 WNC	3.24	10.32	10.16	4.75	0.0900	0.0520	0.0508	0.0817	0.1133	0.0906	0.0770	0.1077
	5 SATL	4.61	8.64	13.36	5.49	0.0842	0.0669	0.0467	0.0804	0.1102	0.0980	0.0775	0.1073
	6 ESC	3.63	10.48	9.49	5.27	0.0949	0.0562	0.0414	0.0842	0.1170	0.0967	0.0648	0.1098
	7 WSC	4.21	7.96	8.66	5.12	0.0562	0.0405	0.0388	0.0524	0.0856	0.0716	0.0601	0.0817
	8 MTN	5.86	12.76	13.04	7.30	0.0805	0.0512	0.0492	0.0743	0.1210	0.1018	0.0826	0.1161
	9 PAC*	3.13	7.99	7.60	4.12	0.1032	0.0846	0.0772	0.0989	0.1264	0.1121	0.0968	0.1227
	10 CA	7.99	9.68	10.88	8.25	0.1475	0.1459	0.0869	0.1462	0.2043	0.1845	0.1153	0.2003
Summer	0 USA	6.14	9.81	11.09	6.95	0.0908	0.0696	0.0534	0.0857	0.1315	0.1071	0.0807	0.1252
	1 NE	11.65	13.62	14.51	11.96	0.1284	0.1001	0.0925	0.1240	0.1887	0.1525	0.1291	0.1827
	2 MATL	13.74	13.22	12.91	13.65	0.0775	0.0491	0.0465	0.0729	0.1706	0.1005	0.0795	0.1587
	3 ENC	4.87	7.45	10.09	5.65	0.0881	0.0771	0.0652	0.0847	0.1262	0.1064	0.0897	0.1204
	4 WNC	3.49	11.66	11.32	5.23	0.0932	0.0560	0.0544	0.0851	0.1186	0.0990	0.0833	0.1135
	5 SATL	4.61	8.65	13.36	5.50	0.0855	0.0678	0.0475	0.0816	0.1111	0.0990	0.0782	0.1082
	6 ESC	3.71	10.57	9.35	5.34	0.0957	0.0565	0.0417	0.0849	0.1182	0.0976	0.0647	0.1108
	7 WSC	4.45	8.55	9.09	5.43	0.0589	0.0415	0.0398	0.0547	0.0892	0.0748	0.0622	0.0851
	8 MTN	6.20	13.77	15.40	7.85	0.0848	0.0530	0.0511	0.0781	0.1273	0.1069	0.0901	0.1223
	9 PAC*	3.13	7.99	7.60	4.12	0.1031	0.0845	0.0770	0.0989	0.1263	0.1120	0.0966	0.1226
	10 CA	10.33	10.03	15.14	10.38	0.1647	0.2081	0.1028	0.1688	0.2342	0.2479	0.1421	0.2342
Winter	0 USA	5.11	8.64	9.65	5.88	0.0842	0.0600	0.0503	0.0789	0.1195	0.0933	0.0740	0.1132
	1 NE	8.51	12.47	14.28	9.14	0.1277	0.1001	0.0923	0.1234	0.1776	0.1482	0.1284	0.1727
	2 MATL	10.95	10.47	9.90	10.85	0.0707	0.0461	0.0457	0.0668	0.1461	0.0871	0.0711	0.1362
	3 ENC	4.30	5.98	8.71	4.87	0.0848	0.0740	0.0625	0.0815	0.1198	0.0977	0.0834	0.1136
	4 WNC	2.99	8.98	9.00	4.28	0.0867	0.0480	0.0473	0.0784	0.1079	0.0822	0.0706	0.1018
	5 SATL	4.60	8.63	13.36	5.49	0.0829	0.0659	0.0460	0.0792	0.1093	0.0971	0.0767	0.1064
	6 ESC	3.55	10.40	9.62	5.20	0.0940	0.0558	0.0411	0.0835	0.1159	0.0958	0.0648	0.1088
	7 WSC	3.97	7.38	8.23	4.81	0.0535	0.0395	0.0378	0.0502	0.0821	0.0685	0.0581	0.0783
	8 MTN	5.51	11.75	10.68	6.75	0.0762	0.0493	0.0472	0.0705	0.1148	0.0966	0.0751	0.1099
	9 PAC*	3.13	7.99	7.60	4.12	0.1032	0.0847	0.0775	0.0990	0.1265	0.1122	0.0971	0.1228
	10 CA	5.65	9.34	6.62	6.11	0.1303	0.0836	0.0709	0.1236	0.1743	0.1211	0.0885	0.1663

Table 13: Annual and seasonal marginal electricity demand and consumption prices, and average prices, by bill group for the EEI data for 2015.

EEI Data 2015		Marginal Demand $/kW				Marginal Energy $/kWh				Average $/kWh			
		A	B	C	D	A	B	C	D	A	B	C	D
		<	100-	>	All	<	100-	>	All	<	100-	>	All
Season	CD/LS	100	1000	1000	Bills	100	1000	1000	Bills	100	1000	1000	Bills
Annual	0 USA	11.63	11.78	10.43	11.60	0.0538	0.0626	0.0556	0.0552	0.1209	0.0973	0.0857	0.1155
	1 NE	12.19	10.35	10.69	11.92	0.0852	0.1292	0.1062	0.0912	0.1781	0.1596	0.1399	0.1748
	2 MATL	13.96	12.31	7.04	13.53	0.0615	0.0723	0.0610	0.0629	0.1431	0.1119	0.0852	0.1373
	3 ENC	7.23	9.27	10.08	7.76	0.0537	0.0610	0.0601	0.0554	0.1120	0.0882	0.0881	0.1063
	4 WNC	9.24	10.78	12.84	9.68	0.0472	0.0627	0.0556	0.0502	0.1029	0.0900	0.0871	0.1000
	5 SATL	12.83	14.48	13.71	13.09	0.0491	0.0554	0.0531	0.0501	0.1141	0.0949	0.0929	0.1106
	6 ESC	11.20	9.36	9.33	10.74	0.0571	0.0716	0.0492	0.0592	0.1216	0.1032	0.0741	0.1151
	7 WSC	8.36	8.27	7.81	8.31	0.0443	0.0523	0.0513	0.0461	0.0986	0.0801	0.0737	0.0939
	8 MTN	17.37	15.35	14.73	16.92	0.0446	0.0477	0.0452	0.0451	0.1153	0.0912	0.0874	0.1101
	9 PAC*	6.46	9.13	6.43	6.88	0.0562	0.0650	0.0591	0.0577	0.1102	0.0894	0.0801	0.1054
	10 CA	20.40	24.82	12.43	20.80	0.0721	0.0806	0.0762	0.0732	0.1749	0.1530	0.1370	0.1716
Summer	0 USA	13.11	12.96	11.58	13.01	0.0549	0.0630	0.0566	0.0562	0.1261	0.1012	0.0887	0.1204
	1 NE	13.15	10.80	10.93	12.80	0.0687	0.0864	0.0775	0.0711	0.1508	0.1179	0.1118	0.1457
	2 MATL	16.97	15.00	8.22	16.45	0.0604	0.0629	0.0513	0.0604	0.1490	0.1100	0.0804	0.1419
	3 ENC	7.38	9.26	10.39	7.89	0.0545	0.0609	0.0606	0.0560	0.1140	0.0886	0.0887	0.1080
	4 WNC	10.24	13.02	14.87	10.94	0.0522	0.0693	0.0625	0.0555	0.1139	0.1025	0.1001	0.1113
	5 SATL	12.96	13.22	14.09	13.04	0.0504	0.0624	0.0596	0.0524	0.1152	0.0970	0.0948	0.1119
	6 ESC	12.13	9.90	9.76	11.57	0.0570	0.0713	0.0493	0.0591	0.1230	0.1044	0.0756	0.1164
	7 WSC	9.36	8.27	8.65	9.13	0.0448	0.0534	0.0527	0.0468	0.1018	0.0829	0.0755	0.0970
	8 MTN	18.48	17.63	18.08	18.33	0.0462	0.0490	0.0458	0.0466	0.1200	0.0983	0.0950	0.1154
	9 PAC*	6.05	8.48	6.57	6.46	0.0559	0.0639	0.0584	0.0573	0.1092	0.0877	0.0787	0.1043
	10 CA	29.55	38.54	22.66	30.52	0.0821	0.0858	0.0804	0.0825	0.2149	0.1963	0.1746	0.2119
Winter	0 USA	10.57	10.94	9.60	10.58	0.0530	0.0622	0.0548	0.0545	0.1172	0.0945	0.0835	0.1121
	1 NE	11.51	10.03	10.52	11.30	0.0971	0.1599	0.1267	0.1056	0.1976	0.1893	0.1600	0.1956
	2 MATL	11.81	10.38	6.20	11.45	0.0624	0.0791	0.0679	0.0647	0.1389	0.1132	0.0885	0.1340
	3 ENC	7.12	9.28	9.86	7.67	0.0531	0.0611	0.0597	0.0549	0.1105	0.0879	0.0876	0.1051
	4 WNC	8.52	9.18	11.39	8.78	0.0437	0.0579	0.0507	0.0463	0.0951	0.0811	0.0778	0.0919
	5 SATL	12.74	15.38	13.44	13.13	0.0482	0.0504	0.0485	0.0485	0.1134	0.0934	0.0915	0.1098
	6 ESC	10.54	8.97	9.03	10.15	0.0572	0.0717	0.0492	0.0593	0.1207	0.1023	0.0731	0.1141
	7 WSC	7.65	8.27	7.20	7.73	0.0439	0.0515	0.0504	0.0456	0.0963	0.0782	0.0724	0.0917
	8 MTN	16.58	13.72	12.34	15.92	0.0434	0.0468	0.0448	0.0440	0.1120	0.0861	0.0820	0.1064
	9 PAC*	6.75	9.59	6.32	7.18	0.0564	0.0657	0.0595	0.0580	0.1109	0.0905	0.0810	0.1062
	10 CA	13.87	15.02	5.13	13.85	0.0650	0.0769	0.0732	0.0666	0.1463	0.1221	0.1101	0.1427